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Feature extraction and classification for Brain-Computer Interfaces

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Feature Extraction and Classification for Brain-Computer Interfaces

Ph.D. Thesis

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Preface

This manuscript describes the work carried out during my Ph.D. studies at the Center for Sensory-Motor Interaction (SMI), Aalborg University, Denmark (years 2004-2008) and at The Santa Lucia Foundation, Scientific Institute for Research, Hospitalization and Health Care, Rome, Italy, where I spend my internship during the period February 2005 - August 2005.

I would like to thank my supervisor Assoc. Prof. Kim Dremstrup for his guidance and confidence in my work. I also thank Ph.D. Febo Cincotti and Assoc. Prof. Fabio Babiloni for receiving me at the department of clinic phisiology of the Santa Lucia hospital in Rome, where I got a great deal of knowledge in BCI systems. Last but certeainly not least I would like to thank Prof. Dario Farina for his guidance and his valuable feedback on my work.
I would also like to thank to the technical and administrative staff at SMI, whose efficiency and kindness made my stay at the SMI a very rewarding and pleasent experience, both in professional and personal levels.

To my family.

Alvaro Rodrigo Fuentes Cabrera
Aalborg, December 2009.

Abstract

In this Thesis three neurological phenomena are investigated and used in two different Brain-Computer Interface (BCI) systems. These neurological phenomena are Steady-State Visual Evoked Potentials and the electroencephalographic patterns produced by auditory and spatial navigation imagery.

In the first chapter the aims and description of the Thesis are included. The second chapter is composed of a review of the relevant literature, and a description of relevant technologies (bio-recording and signal processing) and neurological phenomena, used to drive BCI systems. Chapter 3 is a description of a matlab toolbox for analysis and design of BCI systems, which was developed for the studies in Chapters 4 , 5 and 6. Chapter 4 is a technical report which describes a BCI system based on SS-VEP and its application on augmentative communication and mobilization. Chapters 5 and 6 explore different approaches to feature extraction, selection and classification methods for a BCI system based on Auditory and Spatial Navigation Imagery.

The MATLAB toolbox described in Chapter 3 was used for the development of the online BCI system based on SS-VEP described in Chapter 4, which can produce 9 different command signals. This system was tested on healthy subjects and showed a classification accuracy of 79.74 % (57-100 %) with an Information Transfer rate of 21 bits/min.

The manuscript in Chapter 5 assesses three approaches to feature extraction for a BCI driven by non-motor imagery. The tasks studied in this paper were auditory and spatial navigation imagery which were recorded from 19 naïve subjects. The results of this study show that features extracted using an optimization procedure for the Discrete Wavelet Transform (DWT) produce higher classification rates than those obtained by features extracted with common DWT analysis and autoregressive (AR) modeling. The average classification accuracy using the optimization procedure for the DWT was 70.1 % (63.3-83.3 %). The study in Chapter 6 investigates two methods for classification of auditory and spatial navigation imagery: Bayesian classifier and support vector machine. Features were extracted using AR modeling and optimized DWT and selected with exhaustive search, from the combination of 2 and 3 channels, and with a discriminative measure (r^2). The results showed that both classifiers provided similar classification accuracies. Conversely, the exhaustive search of the optimal combination of features from 2 and 3 channels significantly improved the performance with respect to using r^2 for channel selection. Using features optimally extracted from 3 channels with optimized DWT, the classification accuracy was 72.2 % (64.7-91.5%).

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Danish abstract/Dansk sammenfatning

I denne afhandling er tre neurologiske fænomenerne undersøgt for anvendelighed ved brug i hjerne-komputer grænseflade systemer (BCI) : Steady-State Visuelt Evokerede Potentialer og EEG mønstrene fremkaldt af henholdsvis auditiv forestilling (imagery) og forestilling af spatial navigering i et kendt rum.
Det første kapitel beskriver målene for arbejdet og giver en kort sammenfatning af afhandlingen. Andet kapitel indeholder oversigt over relevant litteratur, en beskrivelse af relevante teknologier (bio-optagelser og signalbehandling) samt neurologiske principper brugt i BCI systemer. Kapitel 3 er et beskrivelsen af en MATLAB toolbox udviklet til design og analyse af BCI systemer. Denne toolbox er anvendt til de undersøgelser som præsenteres i Kapitlerne 4, 5, og 6. Kapitel 4 er en teknisk rapport som beskriver et BCI systemet baseret på SS-VEP og systemets anvendelser til bedring af kommunikation og mobilisering. Kapitlerne 5 og 6 undersøger forskellige tilgange til udtrækning og selektion af features fra EEG-signalet og klassifikationmetoder til BCI systemer baserede på auditiv og spatial navigering forestilling.
MATLAB tooboxŠen beskrevet i kapitel 3 er brugt i udviklingen af det on-line BCI system baseret på SS-VEP som er beskrevet i kapitel 4. Dette system kan producere 9 forskellige kommandosignaler. Systemet er testet med normale forsøgspersoner og gav en klassifikations nøjagtighed på 79.74 % (57-100 %) og en informations overførsel på 21 bits/min.
Manuskriptet i kapitel 5 undersøger tre forskellige metoder til feature ekstraktion i et BCI baseret på non-motoriske "billeddannelser". De undersøgte opgaver var forestillet auditiv og spatial navigering som blev registreret via EEG optaget fra normale naive forsøgspersoner. Resultater viser at de features der opnås ved brug af optimeret Diskret Wavelet Transformation (DWT) giver højere klassifikations rate end de der fås med features fra almindelig DWT analyse og autoregressiv (AR) modellering. Den gennemsnitligeklassifikations nøjagtighed ved optimeret DWT var 70.1 % (63.3-83.3 %). I Kapitel 6 beskrives to klassifikationsmetoder anvendt på data fra forestillet auditiv og spatial navigering: Bayesian classifier og support vector machine. Features fra dette arbejde blev ekstraheret ved AR modellering og optimeret DWT og selekteret med exhaustive search, ud fra kombination af hhv. 2 og 3 kanaler og med r-square ($r2$) metoden til diskriminering mellem målingerne. Resultaterne viste at de to klassifikationmetoder gav sammenlignelig nøjagtighed. Til gengæld viste exhaustive udvælgelse af den optimale kombination af karakteristikaene fra 2 til 3 kanaler at give en significant forbedring af de opnåede resultater i forhold til at bruge $r2$ til udvælgelse

af kanaler. Ved brug af karakteristikaene opnået fra 3 kanaler med optimeret DWT blev klassifikations nøjagtigheden 72.2 % (64.7-91.5%).

Contents

Chapter 1

Aims and Description of the Thesis

1.1 Aims of the Thesis

The aim of this Thesis was to study the extraction, selection and classification of features carried by EEG activity evoked by certain neurophysioligical phenomena for the implementation of Brain-Computer Interface (BCI) systems. To address this problem, three milestones were expected to be achieved:

- To understand the functioning of the most used BCI systems and the neurophysiological phenomena used to drive them.
- To implement an online BCI system with high classification rates that could control useful applications, such as augmentative communication and transportation. Steady-State Visual Evoked Potentials (SS-VEP) were chosen to drive this BCI system.
- To optimize the extraction, selection and classification of the features of EEG activity evoked by Auditory Imagery (AI) and Spatial Navigation Imagery (SNI), using adaptive signal processing.

1.2 Description of the Thesis

This thesis describes the design and implementation of an online BCI system based on SSVEP and the study of EEG activity evoked by AI and SNI.

1.2.1 The BCI systems

In order to design an on line BCI system and study the EEG activity evoked by SSVEP, AI and SNI, a modularized toolbox which allows fast and easy exchange of feature extraction, selection and classification methods for Brain-Computer Interfacing analysis was designed and implemented. This toolbox was used in each of the studies in this thesis, and it served as the basis for the development of the on-line BCI system described in chapter 4.
The online BCI system uses visual stimulation consisting of 9 flickering squares, each of which produce a different SSVEP over the visual cortex. These SSVEP's are analyzed and converted into 9 command signals that control a desire application. The design and implementation of this BCI is described in chapter 5.

1.2.2 Neurphysiological Phenomena used to drive the BCI systems

The 3 neurophysiological phenomena used to drive the BCI systems studied in this this thesis were chosen due to the different manner is which they are elicited and their potential usability by individuals with different degrees of disabilities. SS-VEPs are evoked by external visual stimuli, require almost no training for its elicitation, but requires gaze control for practical applications. These characteristics make SS-VEP a suitable neurological phenomenon to be used in BCI systems for individuals suffering from early stages of ALS, spinal chord injury, or other conditions in which the patients have residual control of upper extremities and/or gaze, but might still need alternative control strategies for communication and mobilization. On the other hand, AI and SNI are induced by spontaneous input and require no muscle activity for its elicitation, what could make them, after a training period, suitable neurological phenomena to be used in BCI systems for locked-in patients.

1.2.3 Signal Processing

The highly characteristic frequency patterns elicited by SS-VEP and its high frequency to noise ratios allow the implementation of a BCI system using simple signal processing techniques. The Fast Fourier Transform (FFT) has been used for feature extraction and a threshold based rule for classification. On the other hand, for the implementation of the BCI system based on non-motor imagery, advanced signal processing was necessary to differentiate between the two classes used in this system. An optimal feature extraction method was specifically chosen for each of the subjects participating on the experiment using an optimization algorithm and two classification procedures.

1.2.4 The chapters

This Thesis is composed of six chapters. Each manuscript includes its own Bibliography and can be read independent from each other. A description of each chapter, excluding the present one, is given as follows:

Chapter 2: Background and Literature Review

In this chapter the context in which the BCI research is carried out is described. The concept of a BCI system is defined and several ways of classifying a BCI system, according to specific design attributes, are described. A literature review is also included. This chapter provides the reader with a theoretical background and an extensive bibliography, both to help to understand the four studies described in Chapter 3, Chapter 4, Chapter 5 and Chapter 6.

Chapter 3: The Smario Toolbox for Brain-Computer Interfacing analysis and design

In this manuscript the Smario toolbox developed for the studies in Chapters 4, 5 and 6 is described. Available signal processing modules are briefly described and examples on how to use them to create customized BCI systems are given. Using this short introduction to the Smario toolbox the reader will understand how the signal processing procedures used in chapters 4, 5 and 6 were designed, and in conjunction with the user manual included with the software, the reader will be able to reproduce such procedures and apply them to his/her own signals.

Chapter 4: Steady-State Visual Evoked potentials to drive a Brain-Computer Interface

Three experimental studies are described in this chapter; all of them form part of the implementation of an online synchronous BCI system based on SS-VEP. In the first study, three subject were presented with single and bi-frequency visual stimulation in order to find out which of these two stimuli gives a more recognizable spectra. The second study was focused on the development of a classifier for the stimulation paradigm that consists of nine different squares flickering at different frequencies on a CRT screen; seven healthy subjects took part on this study. The last study tested the online system implemented using the research done on the first two studies. Seven naïve healthy subjects participated on this experiment.

Chapter 5: Auditory and Spatial Navigation Imagery in Brain-Computer Interface using Optimized Wavelets

In this study two non-motor imagery cognitive tasks were investigated to drive a BCI system; Auditory Imagery of a familiar tune and Spatial Navigation Imagery through a familiar environment. The main aim of this research was to evaluate which feature extraction method extracts features that could be best differentiated, thus, produce the highest classification rate. The secondary goal was to determine which EEG-channels are best suited for classification. Nineteen naïve healthy subjects participated in this experiment and EEG activity was recorded from 18 electrodes over their temporal and parietal lobes. The features used were autoregressive and reflection coefficients extracted using autoregressive modeling (burg-lattice method) with several model orders, and marginals of the wavelet spaces generated by the Discrete Wavelet Transform (DWT). An optimization algorithm with 4 and 6 taps filters and mother wavelets from the Daubechies family were used. The classification was performed for each single channel and for all possible combination of two channels using a Bayesian Classifier. An Erratum to the original manuscript is included as a section.

Chapter 6: Comparison of feature Selection and Classification methods for a Brain-Computer Interface driven by Non-Motor Imagery

This paper presents a comparison of feature selection and classification methods for an EEG based Brain-Computer interface driven by non-motor imagery. Two non-motor imagery tasks were studied, namely, auditory imagery and spatial navigation imagery. Features were extracted using autoregressive modeling and optimized discrete wavelet transform. The feature selection was carried by exhaustive search, method which produced feature vectors composed of two and three channels, and r^2. Two classification methods were assessed, Bayesian classifier and a support vector machine with optimization of the Gaussian kernel and of the regularization parameter.

Chapter 2

Background and Literature Review

2.1 Introduction

The way that humans interact with computers has greatly evolved since 1951, when the first commercial computer, the UNIVAC, made its appearance. This complicated piece of machinery, designed by John Presper Eckert & John W. Mauchly, occupied more than 35.5 m^2 of floor space, the only way to control was a modified IBM electric typewriter, and feedback to the user was given trough a Tektronix oscilloscope. Modern computers are completely mobile and even though they are mainly controlled by a mouse and a keyboard, several alternative human-computer interfaces have been developed during the last two decades using haptics, voice and gaze. People suffering from neuromuscular diseases, such as hemiplegia or hemiparesis, can highly benefit from these technologies, since a computer could allow them to perform multiple tasks. With a computer people can have access to entertainment (Video Games, Books, Music, Movies, Cameras, etc...), communication (Internet, I.P. telephony, e-mails, newspapers, text processors, predictive text programs, speech synthesis, etc...) and means of research (Computational capacity, programming languages, simulation applications, etc...). Further more, nowadays a computer can control pretty much any electronic device, from televisions, DVD and CD players to electric wheel chairs, elevators, doors and lights. So if we stop a second to think about it, we would realize that controlling a computer could provide people with disabilities with most of the necessary means for transportation, interaction with people in their surroundings and over the Internet, and satisfaction of their intellectual needs. Human-computer interfaces like eye tracker, through gazing, and speech recognition engines, through speech, allow persons with hemiplegia and hemiparesis to interact with computers, and if the person has some motor control in at least one of his/her limbs, a Joysticks could do the work, as the remarkable British physicist, Stephen Hopkins, has proven in innumerably occasions by controlling his wheel chair and a text processor to transport him self and communicating his thoughts to others in his conferences around the world. So what happens if you are not able to control any of these human-computer interfaces? Unlike people suffering from hemiparesis, hemiplegia or early stages of ALS, persons with severe motor disabilities, such as advanced stages of ALS, brainstem stroke or severe cerebral palsy, can not control such devices as joysticks, eye trackers or speech recognition engines, since they do not have enough control of their muscles to voluntarily move a limb, articulate a word or gaze at a desire location. They are compelled to live in complete social isolation, not being able to talk or to move, being still conscious and perfectly capable of reasoning. Due to the nature of these diseases no physical rehabilitation is possible. Beside research on prevention and cure, many efforts to give a better quality of life to these persons are concentrated on develop a non muscular based control and communication system which use EEG signals as input: what we call a Brain-Computer Interface (BCI). A BCI system uses mental activity, voluntarily produced by the patient, to control a computer or an embedded system which allow communication or interaction with the surrounding environment. The central element of a BCI is the translation algorithm, which converts electrical activity from the user's brain into signals that can control a computer or an embedded system to, for example, select letters or icons from a screen, control a flight simulator or control cursor movements. These approaches are new output channels from the

Table 2.1: ADVANCED SEARCH PERFORMED IN WEB OF SCIENCE, From years 1900-1914 to 2008

Search string	Citation databases
ts="brain-computer interface" or ts="brain-machine interface" or ts="brain-computer communication" or ts="brain-machine communication" or ts="direct brain interface" or ts="adaptive brain interface"	Science Citation Index Expanded (SCI-EXPANDED)–1900-present Social Sciences Citation Index (SSCI)–1956-present Arts & Humanities Citation Index (A&HCI)–1975-present)

brain that like the brain's normal output channels should be able to seize the brain's adaptive capacities to get an optimized performance of a desire task (133). This performance depends on the interaction between the user's brain and the system it self, the first one produces the electrical activity measured by the BCI, and the second one translates that activity into specific commands. Thus, the success of a BCI system depends as much on the system it self as on the user's ability to produce distinctive EEG activity. BCI systems can be divided into two groups according to the placement of the electrodes used to detect and measure neurons firing in the brain. These groups are: invasive systems, electrodes are inserted directly into the cortex are used for single cell or multi unit recording, and electrocorticography (EcoG), electrodes are placed on the surface of the cortex (or dura); noninvasive systems, they are placed on the scalp and use electroencephalography (EEG) or magnetoencephalography (MEG) to detect neuron activity.
Due to the wide range of possibilities offered by BCI systems, many researches have been focused on applications other than communication and control for persons with disabilities, and the BCI community has welcome researchers dedicated to, i.e. virtual reality (8)(111)(93), restoration of movements of paretic limbs (14)(15), gaming (51)(56)(62) and web surfing (45)(119)

The private sector has also shown interested on this research field. Currently 3 companies commercially distribute systems (hardware and software) which allegedly control applications with brain activity; IBVA Technologies, INC (control digital video movies, music and home automation systems)[1], Emotiv EPOC^{TM} (gaming, simulations)[2] and Smart Brain Games[3] (art Biofeedback and EEG Neurofeedback devices in the areas of Health, Learning and Entertainment).

This chapter consists of a review of BCI systems, the different neurophysiological phenomena used to drive them, and the signal processing applied to these phenomena in order to decode the information carried by them. The BCI systems described in this chapter are

[1]www.ibva.com/ as searched on The Internet, 22-05-2008, no publications available
[2]http://www.emotiv.com/, as searched on The Internet, 22-05-2008, no publications available
[3]http://www.smartbraingames.com/ as searched on The Internet, 22-05-2008, no publications available

classified according to its design attributes, following the framework proposed by Manson et al.(63)(61). systems.
Publications cited in this review, which have been found using the specific search described in Table 2.1 are shown in normal type, e.g. (38), while publications which were not found using the search described in Table 2.1, are shown in bold type, e.g. **(38)** (this publications are either known historical BCI publications or were cited in publications found in our search).

Two appendices complement the scientific background provided in this chapter: (Appendix A) A description of the evolution of BCI research through the years, including relevant bibliography and statistics regarding number of publications per year and institutions involved in BCI research, and (Appendix B) A list of reviews and special issues on Brain-Computer Interfacing.

2.2 Definition, Description and classification of BCI systems

A brain computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles(133). In other words, a BCI system relies solely on mental activity to control a computer on an embedded system, which control a certain application for communication, transportation or any other need of the user. To achieve this, BCI systems use several techniques to differentiate among different mental tasks. According to these techniques or characteristics, which from now on we will call design attributes, BCI systems can be categorized as follow:

- Dependent or Independent, described in section 2.2.1
- Synchronous or Asynchronous, described in section 2.2.2
- according to the neurological phenomena used to drive the BCI system, described in 2.2.4
- according to its bio-recording technology
- feature extraction method
- feature selection method
- feature translation method
- Output device

the design attributes listed above, in which we focused our analysis, are just a small part of the entire list proposed by Mason et al. in (63), which are used in a comprehensive survey of the BCI technology from 1973 until 2006 (61). The design attributes listed above will be described in the following sections.

2.2.1 Dependent and Independent BCI systems

A BCI system does not send the commands to control a computer through the brain's normal output pathways of muscles and nerves, but activity in these pathways might be needed to generate the necessary brain activity (134). According to weather or not the subjects use muscle or nerve activity to produce brain activity, the BCI system falls in one of these two categories: dependent or independent. A dependent BCI does not carry the messages or command through the brain's normal outputs, but activity in these pathways is necessary to produce the brain activity that does carry the information. Good examples of this kind of BCI are most VEP (129)(127), SSV-EP based BCI's (121)(21)(38)(80), which carry the information through EEG activity that is recorded over the visual cortex, but this activity is produced when the subject gaze at a desired character on the screen, as explained in section 2.2.4, and P300 based BCI systems (23)(52)(112), which carry the information through EEG recorded over the parietal cortex, which is elicited when the subject gaze at visual infrequent events, as described in section 2.2.4. To be noticed that Wolpaw et al. in (134) state that P300 BCI systems based on visual infrequent stimuli are independent systems, which is contradicted by Kubler and Muller **(55)**. On the other hand, independent BCI's do not need peripheral nerves and muscles neither to produce nor carry the messages that will control the final application. Most BCI's are considered to be independent, for example the system based on sensorimotor rhythms (101)(90), SCP (99)(40) and Non-motor Imagery (27)(20).

2.2.2 Synchronous and Asynchronous BCI systems

Synchronous systems depend on a protocol that determines the onset, offset and duration of the operations. In other words, they are cue based. For example, the subject is instructed to move the cursor horizontally on the screen, to left or right according to the position of a target; imaginary movements of the right hand will move the cursor to the right and imagination of left hand movements to the left. The appearance of the target informs the subject which is the task to be performed, a few seconds after the appearance of the cursor warns the subject to start the Task that will produce the desired EEG activity, after a period of time, a decision is made by the system (left or right), followed by feedback to the subject about his/her performance. Usually while feedback is given to the subject, the system does not process the EEG activity, thus no decision is made. A synchronous BCI system does not allow the subject to control it at any desired moment, but restrict its use to determined periods of time, during which the EEG signals will be analyzed, and a decision will always be made, whether the subject was using the system or not. Examples of synchronous systems are **(121)(12)**(1)(29). An asynchronous BCI, on the contrary, is always active and beside reacting to the predetermined mental tasks that control the system, is also able to identify a rest state or idle state, whose EEG signals correspond to periods when the subject does not intend to control the system, thus the system does not react and no feedback is given to the subject. Examples of asynchronous systems are (35)(71)(6).

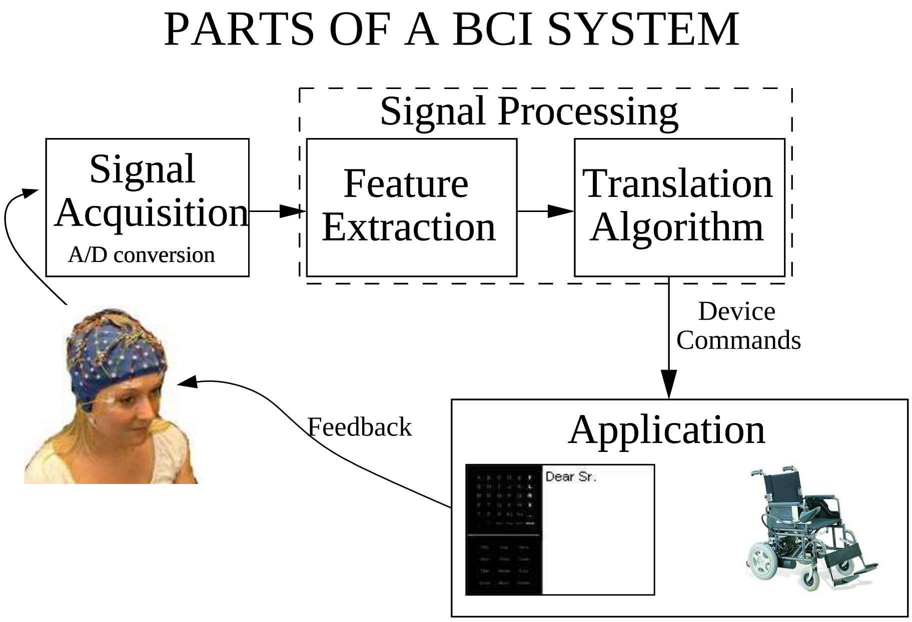

Figure 2.1: Basic dissection of a BCI system. Three main parts are represented: Signal Acquisition, Signal processing and Application. The signal from the brain are acquired using, e.g. electrodes on the scalp (could also be MEG, fMRI or ECoG), amplified and digitized to extract distinctive features (e.g. amplitudes of evoked potentials, sensorimotor rhythms or amplitude of frequency components) which will be after classified and translate into device commands that will control the application (e.g. a speller device or electric wheelchair). The success of the BCI system depends as much on the subject's ability to produce recognizable EEG activity as on the system's efficiency to extract, select and classify this EEG activity

2.2.3 Parts of a BCI system

A BCI is a communication system between the user's brain and a certain application performed in a computer, and like any communication system has an input (e.g. EEG activity from the user's brain) an output (e.g. device commands), components that translate Input into output (translation device) and a protocol that control the timing of the operations (134). Figure 2.1 shows a basic dissection of a BCI system, and the interaction between its parts. The input of the BCI system is achieved by the a certain bio-recording technology, described in Figure 2.1 as the Signal Acquisition Module. This input is processed to extract distinctive features (Feature Extraction Module), which should be able to separate the existing classes after being classified by Translation Algorithm module, which outputs a device command to control the Output Device or Application module. This parts of a standard BCI systems, plus an off-line analysis (feature selection) are described in the following subsections.

Bio-Recording Technology

Different methods to measure brain activity have been used to implement BCI systems. They can be categorized by wether they use non-invasive or invasive methods. By far the most popular is EEG, due to its low cost, high resolution in time and non-invasive characteristics. Several BCI systems have also been developed using other non-invasive methods like magneto-encephalogram (MEG) (18) (67)(46), functional magnetic resonance imaging (fMRI) (132)(138) and near infrared spectroscopic (25) (117). Also studies based on invasive methods have been carried, e.g. based on electrocorticograms (ECoG)(109)(115) (37).

Feature Extraction

Once the brain signals have been digitized they are processed by one or more feature extraction methods. These processes are intended to extract specific characteristics of the signals, which encode the messages or commands elicited in the user's brain by either evoked or spontaneous inputs. Feature extraction methods could either extract information from the signal in time domain, e.g. evoked potential amplitudes (127)(120)(121) or transform the brain signals to be analyzed in different domains, like the frequency domain (22)(110)(20)(33) or time-frequency domain (17)(24).

Feature Selection

The features extracted for its use in BCI systems will provide a better or worse separability for the classes used for control depending on where on the scalp they are coming from and where in its domain they are, e.g. features found in the motor cortex are more likely to provide better separability for classes of a BCI systems based on motor imagery than the features found on the visual cortex, and on the other hand features found on the visual cortex are more likely to provide better separability for classes of a BCI system based on SS-VEP than features found on the motor cortex. Also, for motor imagery based BCI systems, features found on the alpha and beta band are more likely to provide better separability of classes than features found in other frequency bands. So beside the extraction of features using a specific method, is also necessary to select the appropriate features to be used for classification. Feature selection methods are divided into filters methods, e.g. R^2 (66), SEPCOR (19) and wrapper methods, e.g. genetic algorithms (84).

Feature Translation

After features have been extracted and selected, the next step is classification. Several types of classification procedures are used in BCI systems, which can be categorized as linear and non-linear. Linear examples of classifiers are Bayesian Classifiers, LDA and FLD. Examples of non-linear classifiers are Neural networks and SVM. Whether a BCI system uses a linear or a non-linear classifier, its job is not finished after classification, since the output device needs device commands that can relate the classification results with the performance of specific tasks.

Adaptation is another key issue when it comes to the classification procedure. Classification algorithms can adapt in three different levels to a particular user (134):

- Depending on the neurophysiological phenomenon used to drive the BCI system, the classification algorithm adapts to the features produced by that particular neurophysiological phenomenon, e.g. if SSVEP's are used, the algorithm has to adapt to the range of frequency amplitudes (SSVEP) elicited by the visual stimulation.

- A number of factors affect the EEG signals, e.g. mood, time of the day, recent events, illness, fatigue, excitability, hormonal levels, illness. These factors can seriously affect the quality of the features produced by the subject related to a specific tasks. For this reason, the classification algorithm needs a periodic online adjustment to the changes of the EEG features, produced by the factors already mentioned, so it would use the appropriate range of feature values generated by the current user's EEG signals to match the available range of device command values used by the output device.

- The most important level of adaption, is that one that addresses the interaction between the BCI system and the user's brain, both of them being adaptive systems. A subject will learn how to use particular features to control a particular output device, so his/her performance will hopefully improve with training. So the subject will associate a specific neurophysiological phenomenon, elicited either by spontaneous input or evoked inputs, to a specific task, what would engage the brain in a learning process, that as we mentioned before will improve the performance of the tasks, thus the BCI operation. The third level of adaptation addresses this interaction between the learning process, which is reflected on a change in the BCI feature signals, and the changes on the performance of the BCI output, reflected on the accuracy of the performance of the tasks. So the algorithm could respond to an increase of the classification accuracy rewarding the user with faster communication or with tasks that require a more precise performance of the task, e.g. smaller targets.

The Output device

Most BCI systems use a computer screen as output device. In such screen outputs are presented to the subjects in the form of selection of targets (64) or characters (23)(80). Other more advanced outputs have been developed, such as a virtual reality environment where the subject can make an avatar walk (57), video games (51)(56)(62), and web browsers (45)(119). Another type of device outputs have also been used, such as a hand orthosis which can be controlled using motor imagery by subject with cervical spinal chord injury (92).

2.2.4 neurophysiological Phenomena used to drive BCI systems

Several kinds of mental activities may be used to implement a BCI system, they can be divided into two main groups according to how they are generated; using evoked input (e.g. visual evoked potentials and P300) and spontaneous input (e.g. slow cortical potentials, sensorimotor rhythms and Non-motor Cognitive Tasks). IN the following subsection these neurophysiological phenomena are described, and examples of BCI systems that use them are given.

Steady-State Somatosensory Evoked Potential (SSSEPs)

In order to evoke SSSEPs Müller-Putz et al (73) have used transducers to stimulate both index fingers using tactile stimulation in the resonance-like frequency range of the somatosensory system. The vibratory stimulation is reflected on the EEG activity as SSSP, which can be modulated by the subject by either focusing their attention on the right or left finger tips. The first step is to determine the subject-specific resonance-like frequency, which is the optimal frequency of the somatosensory stimulation (76). Subjects were stimulated with their specific frequency stimulation ($ft1$) on the right index finger. On the left index finger a different stimulation frequency ($ft2$) was chosen. Stimulation strengths for both frequencies were set in a manner that the subject found them to be equal. Features from channels C3 and C4 were extracted in the time domain, which were afterwards averaged over a period of time of one second, using a moving average on a sample by sample basis of the past second. The increase on one of the elicited SSSEPs was detected using a linear discriminant analysis (LDA). Two out of four subjects learned to modify their SSSEPs to control a 2-classes BCI system with an accuracy of between 70 % and 80 %.

Visual Evoked Potential (SS-VEPs)

SS-VEP's are elicited by a visual stimulus modulated at a certain frequency; this stimulus produces a response in the EEG activity, which is characterized by oscillations at the stimulation frequency and sometimes at harmonics or sub-harmonics of it. SS-VEP's are easily recognized by analyzing the frequency content of EEG signal recorded over the visual cortex, as shown in Figure 2.3. The visual evoked potentials can be divided into three sub-systems, according to their amplitudes, as seen in Figure 2.2.

The High Frequency Subsystem

This subsystem corresponds to the frequency band between 30 and 60 Hz. The peak response to the flickering stimulus is at the same flicker frequency, so this peak is called the fundamental frequency or the first harmonic. And the peak response for the frequency-doubled is the second harmonic. In this frequency domain the properties are the same whether the response is a fundamental or a second harmonic. It means that the properties of the response are based more on the frequency of the VEP component than on the frequency of the visual stimulus. More over the luminance of the visual stimulus has an effect on the response but not the color.

The Medium Frequency Subsystem

The frequency range of the intermediate subsystem is between 15 and 30 Hz. For a stimuli of 16 Hz the amplitude of the second harmonic is 10 percent less than the fundamental. Two main differences are suggested by Regan (102) between the fundamental and the second

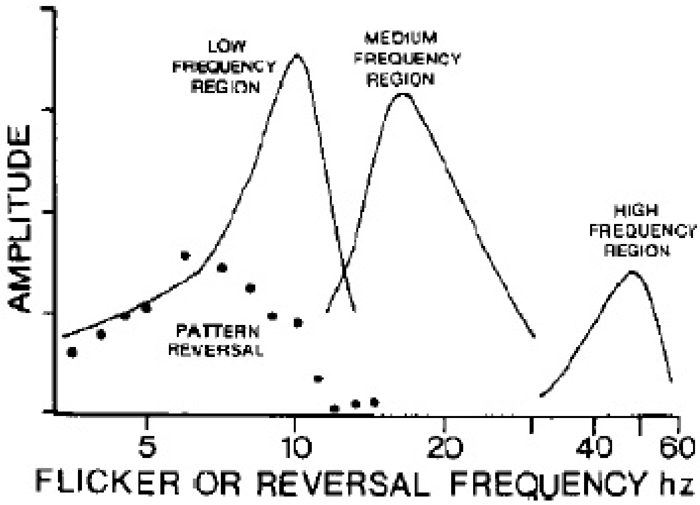

Figure 2.2: SSVEP subsystems. The highest SSVEP amplitudes are observed for the low frequency region. Is in this region were the optimal frequencies for stimulation of SSVEP are found

harmonic. Firstly, the influence of the color, e.g. yellow, where the amplitude of the fundamental is increased but the amplitude of the second harmonic with a 8 Hz flickering stimulus is reduced. Secondly, the amplitude of the fundamental response is much more limited (saturation) by the flicker modulation depth than the harmonic peak.

The Low Frequency Subsystem

The greatest SSVEP amplitudes are observed in this subsystem, in the low frequency band, near the alpha frequency range (8-13 Hz), Hermann (39) demonstrated that the response shows strongest peaks around 10 Hz when light-emitting diodes are used as stimuli.

The first attempt of a BCI system based on SS-VEP was made by Sutter in 1984 (120). The visual stimulation consisted of 128 flickering squares, with electronically superimposed labels displayed on a CRT monitor. The best subject showed an average response time of 1.5 seconds per character scoring approximately 90% of classification accuracy. Since the publication of this research many other have been issued, most of them relying on power spectrum to extract features and using different types of hardware to deliver the visual stimulation.

BCI's based on SS-VEP presents the subjects with a screen where is being display an arrangement of objects separated in space and flickering at different frequencies, each of them with a particular label, which allows the subject to relate the object to a particular character or application. Most available systems, (121), (21)(38), (80), have several characters spread over the entire screen, which makes very difficult eliciting recognizable potentials in the EEG activity without gazing at the desired location, although has been reported that attention without gazing may also be used to control BCI, but using only two characters instead of several (3) and (49). The required training time to achieve acceptable control of the BCI system is little or none when using SS-VEP, unlike MI or SCP, which require days or weeks of training.

P300 component elicited by the oddball paradigm

The P300 is an evoked potential elicit in the EEG activity over parietal cortex, produced by an infrequent event, which can be auditory, visual or somatosensory, among frequent events. The P300 is a positive component, elicited after 300 ms of the infrequent event, as shown in Figure 2.3B. This response to infrequent events is known as the "oddball paradigm", and it was first used to drive a BCI system by Farwell and Donchin (34);(29). The user is presented with a CRT monitor displaying a 6x6 matrix of letters/1-words commands, where each column and row flashes alternatively every 125 ms. The user makes the selection by counting how many times the column or row containing the desired character was flashed. Other groups have conducted studies in order to improve the system described by Farwell and Donchin, such as (4), (114) and (112). Other studies have been focused on the development of new applications, such as (100) which moves a virtual object fro a starting point to a desired location, (7) which control several objects and commands in a virtual 3D environment.

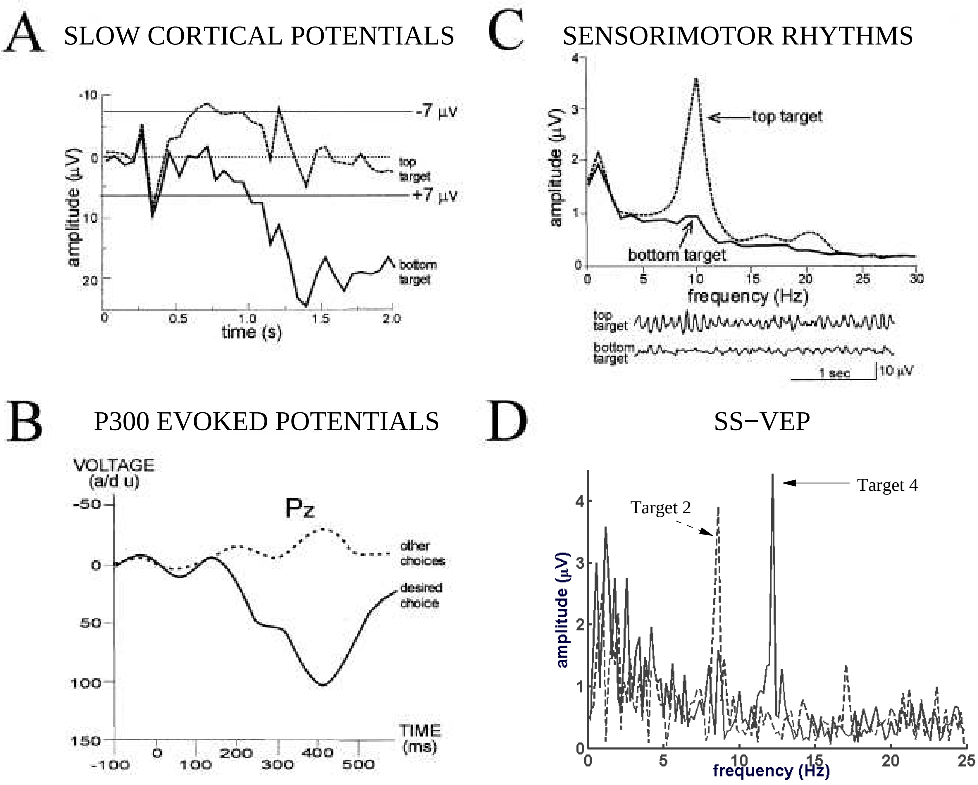

Figure 2.3: Present-day BCI system types (Adapted from (134)). (A)SCP BCI.Scalp EEG is recorded from the vertex. Users learn to control SCPs to move a cursor toward a target (e.g. a desired letter or icon)at the bottom (more positive SCP)or top (more negative SCP) of a computer screen ((54);(12)).(B) P300 BCI. A matrix of possible choices is presented on a screen and scalp EEG is recorded over the centroparietal area while these choices flash in succession. Only the choice desired by the user evokes a large P300 potential (i.e. a positive potential about 300 ms after the flash)((34);(29)).(C) Sensorimotor rhythm BCI.Scalp EEG is recorded over sensorimotor cortex. Users control the amplitude of a 8-12 Hz mu rhythm (or a 18-26 Hz beta rhythm) to move a cursor to a target at the top of the screen or to a target at the bottom (or to additional targets at intermediate locations). Frequency spectra (top) for top and bottom targets show that control is clearly focused in the mu-rhythm frequency band. Sample EEG traces (bottom) also indicate that the mu rhythm is prominent when the target is at the top and minimal when it is at the bottom ((136), (137);(65)). (D) SS-VEP BCI. A matrix of possible choices is presented on a screen and scalp EEG is recorded from the visual cortex while these choices flash at different frequencies. Only the choice desired by the user elicit a SS-VEP at the frequency of the choice or one of its harmonics, in this case two SS-VEP are shown, at 8.5 Hz and 12.14 Hz, each of them separately elicited ((121);(21);(80)).

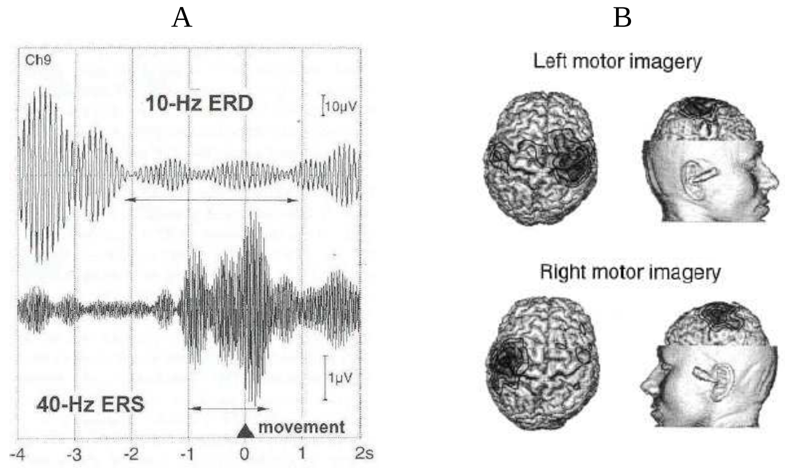

Figure 2.4: (A) Examples of bandpass Filtered EEG trials from voluntary finger movement displaying desynchronization of mu rhythms and an embedded burst of gamma band oscillations.(B) Example of ERD maps for a single subject calculated for the cortical surface of a realistic head model for motor imagery, notice that the activity is contralateral to the movement. Adapted from (42)

Sensorimotor Rhythm Control (SRC)

People in awake state, which is not engaged in processing sensory input or producing motor output, display 8-12 Hz (Mu) and 18-26 Hz (Beta) EEG rhythms over the primary sensorimotor cortical areas. These EEG rhythms are blocked by active movements and also by its mental representation. A decrease of oscillatory activity in the alpha and beta frequency bands is known as Event Related Desynchronization (ERD (87), usually produced by movements or preparation of movements and contralateral to the motor activity, as shown in Figure 2.4B. A phasic enhancement of rhythmic activity is known as Event Related Synchronization (ERS (94)), and is usually occurs after movement and with relaxation (86). Both responses in time domain are depicted in Figure 2.4A. BCI systems based on SRC make use of the decrease/increase in Mu and Beta rhythms in the EEG signals due to motor activity. These responses are typically detected by power spectrum analysis as shown in Figure 2.3 C. The subjects are trained to learn to control their Mu and beta rhythms, mainly by performing motor imagery (i.e. right hand imaginary movement moves the cursor to the right and left hand imaginary movement moves the cursor to the left). The leading groups on this kind of BCI systems are the Wadsworth Center (136);(65) and the Graz group (95). The later group has also developed a system that allows a tetraplegic to control a hand orthosis using motor imagery (92).

Slow Cortical Potentials (SCP)

SCPs are EEG oscillations lasting several hundred milliseconds or several seconds (i.e. slower than usual EEG rhythms). Negative SCPs are typically associated with movements and other functions involving cortical activations, while positive SCPs are associated with reduced cortical activation (134). The ability of humans to control their SCPs has been demonstrated by Birbaumer and colleges in several studies (32)(11);(104). These studies were the base for the BCI system known as the Thought Translation Device (TTD). This system has been extensively tested in people suffering from acute stages of ALS as well as healthy subjects, providing them with basic communication capabilities, like a spelling device (40), and a web browser (45). The training sessions are based on visual feedback, where the subject can monitor the negativity/positivity of the EEG signals, this way the subjects learn how to adjust their brain activity. Figure 2.3A shows a positive and a negative SCP, each of them associated with a letter icon. It is also possible to operate this BCI system in a way that the feedback is given by audible or tactile stimuli (12). The training period may last weeks/months, considering training sessions of 1-2 h/week.

Non-Motor Cognitive Tasks

Several mental tasks, such as multiplication, object rotation, letter composition and visual counting, show hemispheric specialization and are easily recognized using power spectrum or Autoregressive Coefficients of the EEG signals (48). Also numerous studies showed that verbal, analytic, and serial information is processed mainly by the left hemisphere, whereas visual-spatial information is better processed by the right hemisphere (10). Millán et al. have developed a BCI system based on imagination of cube rotation, arithmetic tasks and word concatenating, together with motor imagery (70);(69). The Oxford/London group have also developed a BCI system that uses motor imagery together with a non-motor cognitive tasks, in this case arithmetic subtraction (82);(83). Curran et al., also from the Oxford/London group, investigated different cognitive tasks to drive BCI systems. The task studied were imagination of motor tasks, auditory imagery and spatial navigation imagery (27). Another study on auditory imagery and spatial navigation imagery, using a higher EEG spatial resolution than Curran et al., was perform by Cabrera and Nielsen (20). Both studies suggest that these two task are suitable inputs for BCI systems.

2.3 Conclusions and Discussions

Brain Computer Interface is a relatively new and exiting line of research, in which scientists from different backgrounds work in an interdisciplinary environment to develop systems that are able to bridge brain and computers, to provide persons with disabilities and without them, with new output channels for the brain that do not depend on peripheral muscles and nerves. These new output channels for the brain are intended to control diverse applications, such as augmentative communication, movement restoration and entertainment.
The growth of the BCI community has been reflected on the number of publications issued through the years and the increasing number of institutions that have become involved in BCI research. A very slow increase of publications was observed during the 70's and 80's, followed by a considerable increase of publications during the 90's. In this decades International meetings on BCI technology allowed communication and interaction between groups,

and catapulted an increase on the number of publications due to the apparition of special issues on BCI technology were the works presented during these meetings were published. The technological assessments carried in 2006 and published in 2007 (9) shows that there are abundant and fertile opportunities for worldwide collaborations in BCI research, and reviews like (61) and the present one show that enough and accurate design attributes exist to make BCI systems comparable and categorizable.

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Appendix A: Growth of BCI research through the years

The term Brain Computer Interface was first introduced in 1973, by Professor JJ Vidal from University of California, Los Angeles (UCLA), to describe any computerized system which involved any information obtained from the brain (129). Since this first publication on BCI, 1135 publications have been issued in different journals and specialized magazines until December 04th 2008, according to our search in ISI Web of Knowledge, database: Web of Science[4], described in Table 2.1. 86 % of these publication are articles, the other 14 % corresponding to conference articles, reviews, news and corrections. A detailed list of type of publications is shown in Table 2.2.

Even though the first research was published in 1973, only 4 publications were issued during the entire 70's (129), **(128) (127)** and (118)(News), all from the UCLA, The Brain Computer Interface Project. The first publication by Vidal, (129), was intended as a first attempt to evaluate the feasibility and practicality of utilizing brain signals as command to control computers while developing a novel tool (which implementation started late in 1971 and at the time of publication was still underway), at the time, to study neurophysiological phenomena. A functional dependent on-line BCI system was finally described in 1977, **(128)**, which used VEP's recorded over the visual cortex to move a cursor through a 2 dimensional maze, based on the direction that subject gazed. Beside these 4 publications on BCI other 4 publications, which did not include any BCI system but that would have a huge impact on BCI research in the following years, were published by Pfurtscheller et al.; **(87) (85)(88)** and **(89)**. These publications describe the basics of Event Related Desynchronization (ERD) due to movement preparation, a neurological phenomenon which is used to drive several BCI systems over the world (130)(131)(78)(97)(58)(90)(80).
During the 80's the number of publication did not increased significantly, only 4 manuscripts on BCI were published in this decade, two of them describing actual systems; based on Visual Evoked Potentials (VEP)**(120)** and P300 **(34)**. The other two were a review on

[4]http://apps.isiknowledge.com/WOS
AdvancedSearch_input.do?product=WOS&SID=V1N9HJD1oH8GE5gb@iO&search_mode=AdvancedSearch

Table 2.2: NUMBER AND PERCENTAGE OF PUBLICATIONS BY PUBLICATION TYPE. (according to the search described in Table 2.1)

Document Type	Record Count	% of 1135
PROCEEDINGS PAPER	613	54.01%
ARTICLE	438	38.59%
MEETING ABSTRACT	36	3.17%
REVIEW	30	2.64%
EDITORIAL MATERIAL	13	1.15%
NEWS ITEM	3	0.26%
CORRECTION	2	0.18%

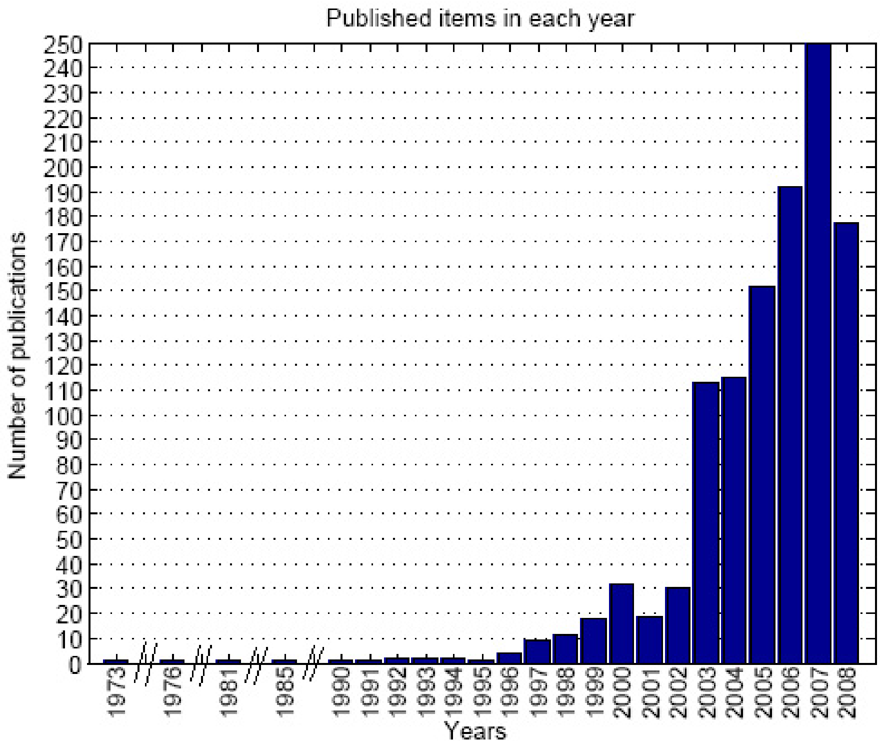

Figure 2.5: Number of publication per Year (according to the search described in Table 2.1)

BCI technology (113) and a technical specification for the devolvement of brain-machines interfaces. (43) Other 4 related to bio-feedback of event-related potentials **(11)** and slow cortical potentials **(32)(10) (104)**.
Things changed dramatically in the 90's, decade where the number of publication raised exponentially, as seen in Figure 2.5. The number of publication per year with its respective percentages can also be seen in Table 2.3. In this decade 51 publications were issued, including BCI systems based on P300 (28), sensory-motor rhythms (135)(136), Evoked related Desynchronization (ERD) (91)ISI:000076546700134, Steady State Visual Evoked Potentials VEP **(121)** and Slow Cortical potentials (SCP) (53). By 1995 there were no more than six active BCI groups in the world, scenario that changed drastically by year 2000, when there were already more than 20 (133). Was at the beginning of the first decade of the 21st century, almost two decades after the first definition of BCI, that the term BCI was re-defined by Wolpaw et al. (133); *A brain computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles.* The review containing this definition was included in a special issue of the IEEE Transaction on Rehabilitation Engineering, dedicated to the first international meeting on BCI technology, which was organized by the Wadsworth Center of the New York State Department of Health and took place in June of 1999 at the Rensselaerville Institute near Albany, New York. Fifty scientist and engineers from 22 research groups participated in

Table 2.3: NUMBER AND PERCENTAGE OF PUBLICATIONS BY PUBLICATION YEAR. (according to the search described in Table 2.1)

Publication Year	Record Count	% of 1135
1973	1	0.09%
1976	1	0.09%
1981	1	0.09%
1985	1	0.09%
1990	1	0.09%
1991	1	0.09%
1992	2	0.18%
1993	2	0.18%
1994	2	0.18%
1995	1	0.09%
1996	4	0.35%
1997	9	0.79%
1998	11	0.97%
1999	18	1.59%
2000	32	2.82%
2001	19	1.59%
2002	30	2.64%
2003	113	9.96%
2004	115	10.13%
2005	152	13.39%
2006	192	16.92%
2007	250	22.03%
2008	177	15.6%

this meeting. Four years later the third International Meeting on BCI Technology was being held again in the proximities of Albany, this time 53 laboratories presented their research, and four workshops were carried addressing four specific topics crucial to the continuing progress of the BCI research and development (125). In the three first years of the present decade more manuscripts were published on BCI than in the period expanding from 1973 to 1999, as it can be seen in Table 2.3 and Figure 2.5.

Only six countries participated in the first international meeting on BCI technology in 1999 (Austria, Canada, Germany, Great Britain, Italy and United States). Nowadays four-hundred and eight institutions from fourty-seven countries have participated in at least one of the 1135 BCI related manuscript published until December 04th 2008, as shown in Table 2.4. Out of the 1135 publications issued from 1973 to 2008, only 14 are written in a language other than English; 3 in Chinese (81)(139)(59),3 in Spanish (108)(105)(103),2 in German (98)(96), French(106)(107), 2 in Polish (50)(47), 1 in Russian (68) and 1 in Turkish (41).

In 2007 a delegation of the World Technology Evaluation Center (WTEC)[5], published review and assessment of the state of the art in several fields related to the BCI technology. Research groups in North America, Europe and Asia were assessed, major trends in current and evolving BCI technologies were indetified (9)[6]. The WTEC panel concluded that there are abundant and fertile opportunities for worldwide collaborations in BCI research and allied fields, scenario that is far away from the existing one 20 years ago.

[5]http://wtec.org/

[6]available online: http://www.wtec.org/bci/BCI-finalreport-10Oct2007-lowres.pdf

Table 2.4: NUMBER AND PERCENTAGE OF PUBLICATIONS BY COUNTRY.(according to the search described in Table 2.1) Percentages in this table are not supplementary, since in several publication the authors belong to institutions from different countries(20 records (3.5%) do not contain data in the field being analyzed.)

Country/Territory	Record Count	% of 1135
USA	386	34.01%
PEOPLES R CHINA	131	11.54%
GERMANY	129	11.37%
AUSTRIA	99	8.72%
ITALY	78	6.87%
JAPAN	77	6.78%
CANADA	64	5.64%
ENGLAND	47	4.14%
SINGAPORE	29	2.56%
SOUTH KOREA	29	2.56%
SWITZERLAND	28	2.47%
SPAIN	19	1.67%
FRANCE	18	1.59%
IRAN	18	1.59%
ISRAEL	16	1.41%
AUSTRALIA	15	1.32%
IRELAND	15	1.32%
MALAYSIA	13	1.15%
TAIWAN	12	1.06%
NORTH IRELAND	10	<1%
NETHERLANDS	9	<1%
DENMARK	8	<1%
FINLAND	8	<1%
INDIA	6	<1%
MEXICO	6	<1%
CZECH REPUBLIC	5	<1%
POLAND	4	<1%
PORTUGAL	4	<1%
RUSSIA	4	<1%
BELGIUM	3	<1%
BRAZIL	3	<1%
ROMANIA	3	<1%
SCOTLAND	3	<1%
TURKEY	3	<1%
GREECE	2	<1%
LEBANON	2	<1%
LITHUANIA	2	<1%
ARGENTINA	1	<1%
CYPRUS	1	<1%
NORWAY	1	<1%
PAKISTAN	1	<1%
PERU	1	<1%
PHILIPPINES	1	<1%
SLOVENIA	1	<1%
SWEDEN	1	<1%
UKRAINE	1	<1%
WALES	1	<1%

Appendix B: Reviews and Special issues on Brain-Computer Interfacing

The obvious purpose of articles and meeting abstracts is the dissemination of the research of particular groups, focused on specific topics within a certain research field. Other type of publication, which do not focus its attention on experiments with subjects or the development or methods but rather on the analysis of results of other studies, comparison among or categorization of them, have as function to deliver a source of information for researchers, where they can find an overview of recent progress within a certain research field, focused either on general aspects or specific topics, eg. signal processing, feature selection, artifact rejection or feature classification, in the case of BCI research. In this section we provide a list of a few reviews on BCI technology with a small description of them, which can be found in Table 2.5. Also included are special issues, where a large number of publication on BCI are to be found.

Table 2.5: REVIEWS AND SPECIAL ISSUES ON BCI RESEARCH. NA stand for non applicable. Special issues and publications that were not found in the search described in Table 2.1 are shown in bold type, while publications found within this search are shown in normal normal type

publication	type	focus
(60)	review	classification methods
(2)(13)(16)(107)(30)(134)	review	general overview
(31)	review	Signal Processing
(78)	review	Motor Imagery/Output Devices
(64)	review	sensorimotor rhythms/signal processing
(97)	review	ERD/ERS
(122)	review	feature extraction
(36)	review	artifact rejection
(61)	review	technology design
(72)	review	neuroprostheses control/(a)synchronous systems
(101)	review	Mu rhythms
(26)(54)	review	output devices for severely disable patients
(5)	review	motor control/local field potentials/output devices
(77)	review	sensory input and motor output/ control of neural plasticity
(116)	review	Biopotentials as feedback/FES
(129)	review	Design considerations (First BCI published paper)
(75)(74)(44)(124)(79)(123) (126)	special issues	NA
(9)	technology assessment	Technology Assessment of groups in Europe and Asia

Chapter 3

The Smario Toolbox for Brain-Computer Interfacing analysis and design

Chapter 4

Steady-State Visual Evoked Potentials to Drive a Brain Computer interface

AALBORG UNIVERSITY

Department of
Health Science and Technology

Alvaro Fuentes Cabrera and Kim Dremstrup

Steady-State Visual Evoked Potentials to Drive a Brain Computer Interface

Report *2008:1*

Steady-State Visual Evoked Potentials to Drive a Brain Computer Interface

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Summary

The development of a Brain Computer Interface (BCI) system based on Steady-State Visual Evoked Potentials (SS-VEP) is described in three steps; the design of a visual stimulation paradigm, the design of a classifier, and the on-line implementation of the system. For the visual stimulation paradigm single and bi-frequency stimulation were tested. The single-frequency stimulation showed to elicit higher SS-VEP on the stimulating frequency than bi-frequency stimulation. Based on single-frequency stimulation a simple classifier was developed based on FFT power spectrum amplitude criteria. The on-line system was tested on 7 healthy subjects, giving an overall classification rate of 79.4 %. Finally, the applications in development for this system are described together with future research that will guide us to the implementation of a BCI system capable of providing communication and transportation means for disables persons.

Index Terms— Brain Computer Interface (BCI), Steady-State Visual Evoked potential (SS-VEP), electroencephalographic (EEG) analysis, FFT power Spectrum, Augmentative communication.

A. INTRODUCTION

An electroencephalogram (EEG) based Brain-Computer Interface (BCI) uses electrical signals from the cortex to control external devices like a computer or other systems and is aimed to facilitate communication for subjects with severe motor impairments. As also reported by numerous authors (see [3]), we use the principle of Steady-State Visual Evoked Potentials.

SS-VEP's are elicited by a visual stimulus modulated at a certain frequency, which are enhanced in the EEG activity [2]. We generate a set of 9 symbols, using a standard computer monitor (CRT), which serves as visual stimulation to elicit the SS-VEP. These symbols are displayed on the computer screen using pre-developed software that permits to set any pixel of the screen at any refresh cycle to a specific color.

This document describes the steps that conducted to the implementation of a real time BCI system based on SS-VEP and the applications in development for such a system. Two pilot experiments where conducted in order to design the visual stimulation paradigm and the classifier of the BCI system. The final experiment tested both, visual stimulation (matrix of 3x3 squares, labelled with numbers from 1 to 9) and classification procedure in a real time session where subjects were asked to "dial" their own phone number and select the numbers associated with their birthday.

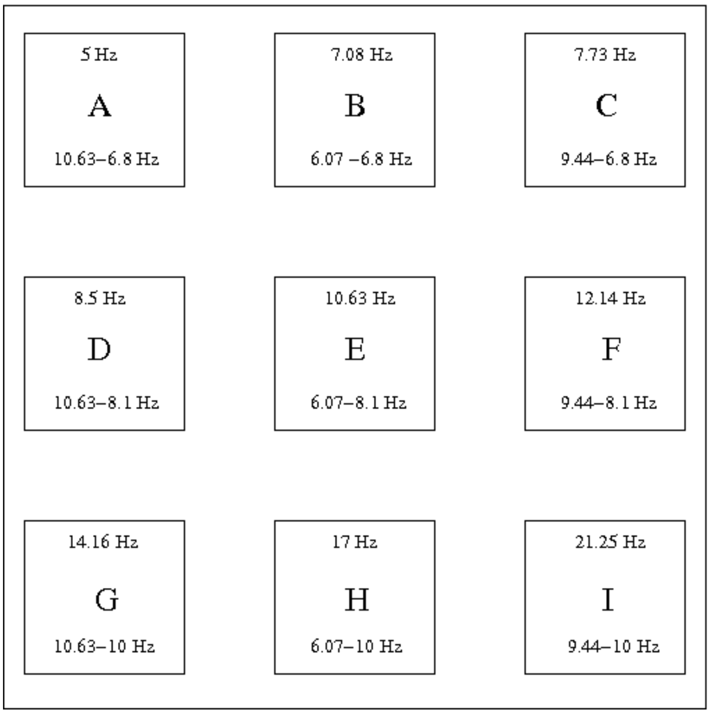

Figure 1: Distribution of the blocks on the screen. On top of each square are the frequencies used for single frequency stimulation. On the bottom of each square are the frequencies used for bi-frequency stimulations. Each square is 4x4 cm and they are separated from each other by 4 cm.

B. EEG SPECTRA USING SINGLE AND BI-FREQUENCY STIMULATION

This experiment is aimed to find out either if single or bi-frequency stimulation give letter spectra. Nine 2x2 cm blocks are settled on the screen.

1. Subjects

Three healthy subjects participate in this experiment, two males and 1 female, between 25 and 31 years old, with normal vision using glasses (subjects 1 and 3) and normal vision (subject 2).

2. Equipment

The EEG data acquisition was performed using the Quick-Cap EEG positioning system, the Nu-Amp digital amplifier and the Scan 4.3 Data Acquisition Software (Neuroscan). Data were sampled at 1000 Hz using a band pass filter set to 0.5-70 Hz, a notch filter at 50 Hz and a standard resolution of 32 bit. The skin impedance was checked four times within the experiment and maintained below 5 kΩ.

3. Visual Stimulation

The visual stimulation consists of a matrix of 3 by 3 yellow squares, labelled with letters from A to I, flickering on a black background, positioned as shown in Fig. 1. The squares are 4 cm^2 and they are separated from each other by 4 cm. The visual stimulation is presented to the subject through a 21 inches CRT (Cathode-Ray Tube) computer screen (Nokia Multigraph 445Xpro) with a refreshment rate of 85 Hz.
Two different visual stimulation paradigms were presented to the subjects, namely bi-frequency stimulation consisting of nine blocks flickering at nine different bi-frequencies and single-frequency stimulation consisting of nine blocks flickering at different single frequency. In the single frequency stimulation paradigm each block flickers at a particular frequency, while in the bi-frequency stimulation paradigm each block flickers at two different frequencies. Figure 1 depicts the screen configurations for the nine blocks and its respective single-frequency and bi-frequency stimulation, on top and bottom of each block respectively. To validate the frequencies delivered by the computer screen were the ones intended the light waves emitted by each square on the screen were recorded using a photo detector connected to an oscilloscope as described in [15]. For each square, 10-s of signal were recorded and the frequency content analyzed. All of the nine squares showed to deliver the right frequencies. For a detailed explanation of how to generate bi-frequency stimulation see appendix 4.

4. Performance of the Task

The subjects sat on a chair with the forehead 50 cm from the centre of the computer screen in a room with no other luminance than the computer screen. For each stimulation paradigm, the subjects were instructed to look at each block for five seconds, each time having an inter stimulus interval equal to five seconds. During the inter-stimulus interval a synthesized voice instructed the subject on which letter to look next. Two seconds after, a 20 ms beep gave the cue to actually look at the number and after 5 s the same cue instructed the subject to stop looking at the block. Each visual stimulation paradigm (single and bi-frequency stimulation) was randomly presented three times to each subject with a rest time of three minutes. Each time the subjects looked three times at each block (the order was randomly selected), what gives a total number of nine 5 s-trials for each single-frequency and bi-fre4quency block.

5. Electrode Placement

EEG signals were recorded from Oz electrode, referenced to the electrode A1 placed on the left ear lobe.

6. Results

The frequencies elicited by the visual stimulation are shown in Tables A1 and A2 (Appendix 1). The amplitudes presented in these tables were obtained by averaging the nine FFT spectrum (4096 points) obtained for each block. When a frequency or by-frequency stimulation shows no amplitude means that the amplitude on that specific frequency was equal or smaller than double the average of all the samples in the spectrum. The results shown in Table A1 (Appendix 1) demonstrates that the bi-frequency stimulation elicits most of the time only one of the two stimulating frequencies, what leads to bad detection since each of the six different stimulating frequencies are used in three different blocks. For example 6.8 Hz is used in blocks A, B and C. Let's take subject 3 for blocks A, B and C, a peak in 6.8 Hz was elicited but for block A a peak in 10.6 Hz was also elicited, thus, B and C have the same feature vector as seen in Figure 2 Left-Top and Right-Top. On the other hand, single-frequency stimulation elicits the fundamental for all the blocks with exception of A, which elicits more harmonics, as seen in Table A2 (Appendix 1) and in Figure 3 Left-Middle and Right-Middle.

The spectra produced by bi-frequency stimulation have much more noise than the ones produced by single-frequency stimulation. Some of the peaks elicited by bi-frequency stimulation correspond to stimulation frequencies related to another blocks, as shown in Figure 2 Left-Bottom and Right-Bottom.

7. Discussion and Conclusions

Bi-frequency stimulation seems to have more noise than single-frequency stimulation and not always both frequencies are elicited. On the other hand single-frequency stimulation produces, in most of the cases, the fundamental frequency in the spectrum, what makes each feature vector unique, and some times some of its harmonics, what could help to develop a personalized classifier, relying on the specific characteristic of the spectra of each subject.

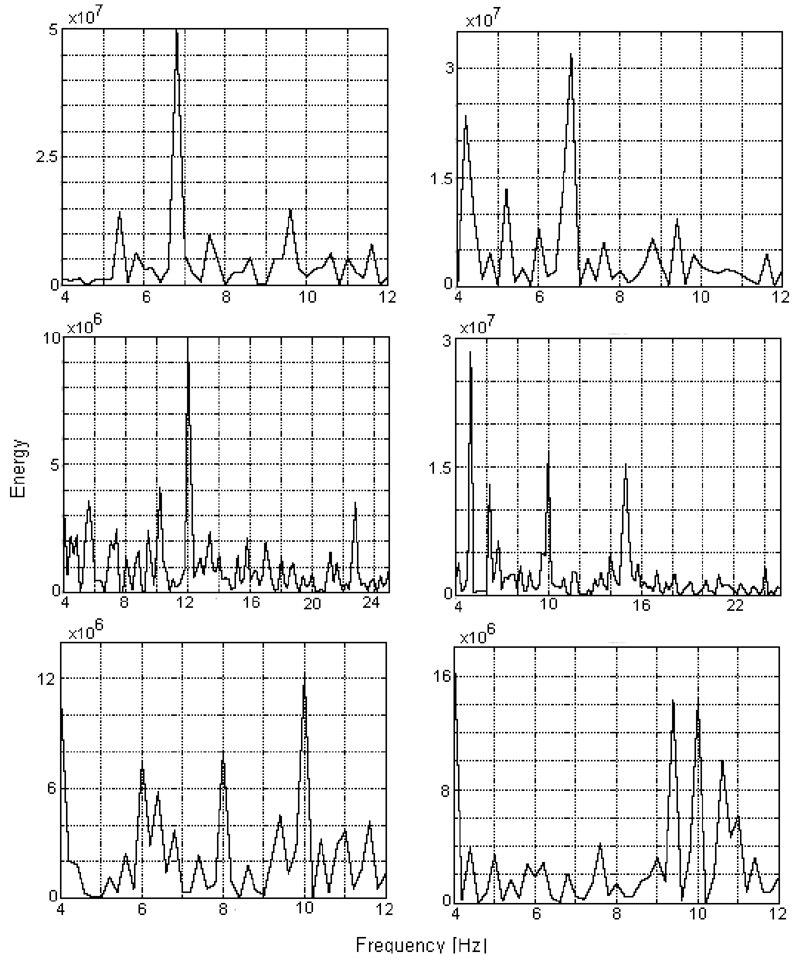

Figure 2: Left-Top Spectra of the block B with bi-frequency stimulation (6.8 and 10.63 Hz). Only 6.8 Hz was elicited. **Right-Top** Spectra of the block C with bi-frequency stimulation (6.8 and 9.44 Hz). Only 6.8 Hz was elicited. **Left-Middle** Spectra of the block F whit single-frequency stimulation. A strong component in 12.02 Hz is elicited, which correspond to the stimulating frequency. **Right-Middle** Spectra of the block A whit single-frequency stimulation. Three peaks are elicited corresponding to fundamental (5 Hz), and its first and second harmonics. **Left-Bottom** Spectra of the block E. The stimulating frequencies of the block E (6.08 and 8.1 Hz) are elicited correctly but 10 Hz, frequency that do not correspond to this block, is also elicited.
Right-Bottom Spectra of the block I. The stimulating frequencies of the block I (9.44 and 10.06 Hz) are elicited correctly but 10.6 Hz, frequency that do not correspond to this block, is also elicited.

C. DEVELOPMENT OF THE CLASSIFIER

Based on the results obtained in Section B, an off-line brain computer interface (BCI) was implemented based on power spectral analysis of single trials of steady-state visual evoked potentials (SS-VEP) elicited by single frequency visual stimulation. The visual stimulation is delivered by a standard computer screen, which presents the user with a matrix of 3 by 3 squares, each flickering at a different frequency and labelled with a number from 1 to 9. The classification made was based on simple amplitude criteria. The result for 7 healthy subjects indicates that the BCI system achieves an accuracy of 92.8 % using 5 seconds of EEG signal and 90.4 % using 3 seconds. The findings described in this section have been partially published in [12]

1. Subjects

Seven healthy subjects (5 male and two female) between 21 and 32 years old (mean 25.4, SD 3.5) participated in the experiment all with normal or corrected vision.

2. Equipment

The EEG data acquisition was performed using the Quick-Cap EEG positioning system, the Nu-Amp digital amplifier and the Scan 4.3 Data Acquisition Software (Neuroscan). Data were sampled at 500 Hz using a band pass filter set to 0.5-70 Hz, a notch filter at 50 Hz and a standard resolution of 32 bit. The skin impedance was checked four times within the experiment and maintained below 5 kΩ.

3. Visual Stimulation

The visual stimulation consists of a matrix of 3 by 3 yellow squares, labelled with numbers from 1 to 9, flickering on a black background at 5, 7.08, 7.73, 8.5, 10.63, 12.14, 14.16, 17, and 21.25 Hz. The position and frequencies of the blocks are the same as in the single-frequency paradigm stimulation described in the experiment in Section B. The squares are 4 cm^2 and they are separated from each other by 4 cm. The visual stimulation is presented to the subject through a 21 inches CRT (Cathode-Ray Tube) computer screen (Nokia Multigraph 445Xpro) with a refreshment rate of 85 Hz.

4. Performance of the Task

The subjects sat on a chair with the forehead 50 cm from the centre of the computer screen in a room with no other luminance than the computer screen. They were instructed to focus their attention on the number in the centre of the square, and to not blur their sight while looking at it. The EEG signals were recorded in segments of 5 seconds. Each trial corresponds to the evoked potential elicited by one of the

TABLE I
Stimulating frequencies with the approximated frequencies used in the recognition software, due to the frequency resolution of the FFT (0.2 Hz).

number	No. trials	Stim.Freq.-Aprox. Freq.	Aprox. 2nd harmonic	Aprox. 3rd harmonic
1	44	5 Hz-5 Hz	10 Hz	
2	49	7.08 Hz -7 Hz	14.2 Hz	21.2 Hz
3	44	7.73 Hz -7.8 Hz	15.4 Hz	23.4 Hz
4	44	8.5 Hz -8.6 Hz		
5	54	10.63 Hz -10.6 Hz	21.2 Hz	
6	44	12.14 Hz -12.2 Hz	24.4 Hz	
7	49	14.16 Hz -14.2 Hz		
8	44	17 Hz -17 Hz		
9	44	21.25 Hz -21.2 Hz		

flickering squares. 63 trials were performed by subjects number one and two and 58 trials were performed by the other 5 subjects.

5. *Signal processing*

The signal processing is based on the fact that the spectrum of the EEG signal elicited on the Oz electrode when the user focuses his attention on a specific number shows its biggest peak on the stimulation frequency or one of its harmonics [3]. FFT power spectrum was applied to 3 and 5 seconds of EEG signal. The number of the FFT in both cases was settled to 2500 (the 3 sec. signals was zero-padded).

6. *Classifier*

The classification procedure was based on simple amplitude criteria applied to the relevant frequencies. These frequencies were written into a vector: *freqvect*=[5, 10, 7, 7.8, 8.6, 10.6, 12.2, 14.2, 15.4, 17, 21.2, 23.4, 24.4]. From these frequencies the two highest peaks along with its respective amplitudes are kept for the classification phase. These frequencies correspond to the simulating frequencies and some of its harmonics, as shown in Table I (Note that the decimal values of the frequencies were approximated to the closest even number, due to the frequency resolution of the FFT). The maximum value in a ratio equal to 0.2 Hz was obtained for each of these frequencies. This procedure is applied since pilot experiments showed that the highest amplitude elicited it may correspond either to the stimulating frequency or to its second or third harmonic, with a deviation of ± 0.2 Hz. As a result of this process another vector of the same dimensions of *freqvect* is obtained. From this vector the two highest amplitudes are taken, along with its corresponding frequency. Based on these two amplitudes and its corresponding frequencies the classification process was carried as explained in following lines:

- Number 1 is recognized if: maximum amplitude corresponds to 5 Hz or 10 Hz
- Number 2 is recognized if: maximum amplitude corresponds to 7 Hz or if the maximum amplitude corresponds to a=14.2 Hz (second harmonic) and the second maximum amplitude corresponds to b=7 Hz, with b>a/3, or if the maximum amplitude corresponds to a=14.2 Hz (second harmonic) and the second maximum amplitude corresponds to b=21.2 Hz (third harmonic), with b>a/3}, or if the maximum amplitude corresponds to a=21.2 Hz (third harmonic) and the second maximum amplitude corresponds to b=7 Hz , with b>a/3, or if the maximumamplitude corresponds to a=21.2 Hz (third harmonic) and the second maximum amplitude corresponds to b=14.2 Hz , with b>a/3
- Number 3 is recognized if: maximum amplitude to 7.8 Hz, 15.4 Hz (second harmonic) or 21.2 Hz (third harmonic)
- Number 4 is recognized if: maximum amplitude corresponds to 8.6 Hz
- Number 5 is recognized if: maximum amplitude corresponds to 10.6 Hz or if the maximum amplitude corresponds to a=21.2 Hz (second harmonic) and the second maximum amplitude corresponds to b=10.6 Hz, with b>a/3
- Number 6 is recognized if: maximum amplitude corresponds to 12.2 Hz or 24.4 Hz
- Number 7 is recognized if: maximum amplitude corresponds to 14.2 Hz
- Number 8 is recognized if: maximum amplitude corresponds to 17 Hz
- Number 9 is recognized if: maximum amplitude corresponds to 21.2 Hz

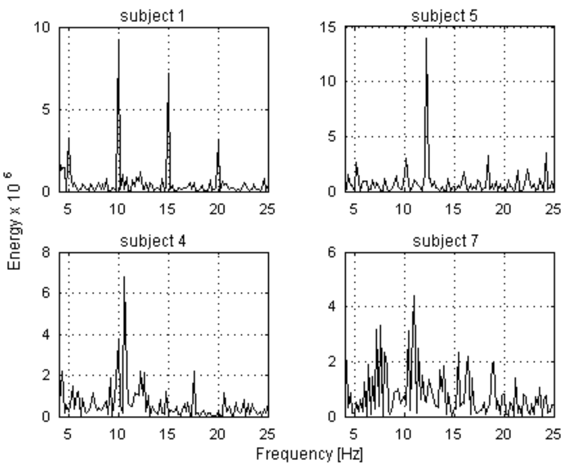

Figure 3: Top Left: Right recognition of Nr. 1. Top Right: Right recognition of Nr. 5. Bottom Left: Looked at Nr. 9 and Nr. 5 is recognized. Bottom Right: Looked at Nr. 9 and Nr. 3 is recognized. (5 sec. EEG signal)

TABLE II
Average accuracy of the BCI system for each of the 7 subjects (over the 9 characters) using 3 seconds and 5 seconds of EEG signal.

Subject	Average Accuracy (5 s)	Average Accuracy (3 s)
Sub.1	98.4 %	98.4 %
Sub.2	95.2 %	93.7 %
Sub.3	93.1 %	86.2 %
Sub.4	93.1 %	89.7 %
Sub.5	98.2 %	93.1 %
Sub.6	98.2 %	96.6 %
Sub.7	75.9 %	72.4 %
grand average	**92.8 %**	**90.4 %**

7. Results

The analysis with 5 seconds over seven subjects showed an average accuracy of the BCI system of 92.8 %. For 3 seconds of EEG signal the average accuracy over seven subjects is 90.4 %. The results for each of the seven subjects are shown in Table II. Spectra leading to right recognition are shown in Figure 3, Top Left: Nr.1 (harmonics of 5 Hz) and Top Right: Nr. 6 (12.14 Hz). Individual recognition rates for each stimulation frequency together with the recognition rates for each stimulation frequency over all 7 subjects are shown in Appendix 2.

8. Discussions

We have studied the performance of an SS-VEP based BCI system, which use the power spectrum of the EEG signals and apply an amplitude detection criterion to classify 9 different commands, voluntarily elicited by the subjects.
The better performance of the system using 5 s is a result of the FFT-based periodogram analysis due to a combination of the inverse proportionality between observation length and resolution, and the improvement of signal/noise ratio obtained with longer observation time.
Subject 7 showed to have a lower recognition rate than the other 6 subjects, specially regarding characters 7, 8 and 9. The wrong detections were mainly caused by blur spectra, with very different frequency content from a normal SS-VEP spectrum. This subject reported to be sleepy and dizzy at the moment of the experiment. Fig 3 (bottom right) shows how subject 7 elicits a number of peaks in frequencies that have nothing to do with the stimulation frequency (21.2 Hz). In this case number 3 was recognized, which stimulating frequency (7.8 Hz) is neither a multiple nor a fraction of 21.2 Hz, the frequency related to number 9. Errors for the other subjects are related to the elicitation of frequencies related with other characters, i.e. number 9 often elicit 10.6 Hz (sub-harmonic) as shown in Fig.2 (bottom left), which is the stimulating frequency for character number 5. Thus number 5 is detected. Same situation occurs with the next two pairs: 9-1 and 2-7, where the former elicits peaks in frequencies related to the later.

9. Conclusions

The results of this study show a high recognition rate for the SS-VEP based BCI, giving nine different commands to control, with no muscle activity but eye movement, any external device, i.e., a word processor for paralysed subjects. The time dependency of the FFT analysis makes it difficult to reduce the time required for an optimal detection, what suggest either a different approach for the spectral analysis, i.e., ARMA modelling or/and a more optimal detection algorithm. In order to avoid wrong classification due to overlapping between stimulating frequencies and sub-harmonics a change in the stimulating frequencies related with numbers 9 and 2 (21.25 and 7.06 Hz) is also necessary.

D. ON-LINE SYSTEM

Based on the results from experiments described in Section B and C an on-line BCI system was developed using single frequency stimulation paradigm and a simple classifier based on amplitudes of FFT spectrum. The findings described in this section have been partially published in [11]

1. Subjects

Seven healthy subjects, six males (two of them with myopia and wearing glasses) and one female participate on the experiment.

2. Equipment

The EEG data acquisition was performed using the Quick-Cap EEG positioning system, the Nu-Amp digital amplifier and the Scan 4.3 Data Acquisition Software (Neuroscan). Data were sampled at 500 Hz using a band pass filter set to 0.5-70 Hz, a notch filter at 50 Hz and a standard resolution of 32 bit. The skin impedance was checked four times within the experiment and maintained below 5 kΩ.

3. Visual Stimulation

The visual stimulation consists of a matrix of 3 by 3 yellow squares, labelled with numbers from 1 to 9, flickering on a black background at 5, 7.08, 7.73, 8.5, 10.63, 12.14, 14.16, 17, and 9.44 Hz. The position of the blocks is the same as in the single-frequency paradigm stimulation described in the experiments in Section B and Section C and depicted in Fig. 1. The squares are 4 cm^2 and they are separated from each other by 4 cm. The visual stimulation is presented to the subject through a 21 inches CRT (Cathode-Ray Tube) computer screen (Nokia Multigraph 445Xpro) with a refreshment rate of 85 Hz.

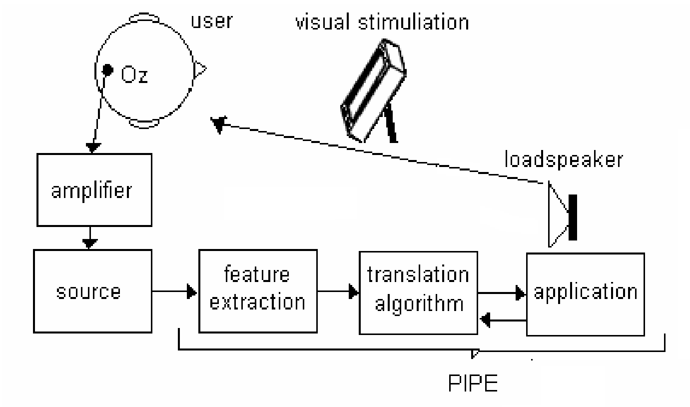

Figure 4: Parts of the implemented BCI system. The pipe consists of three different modules: feature extraction, translation algorithm and application. The amplifier acquires and digitizes the EEG potentials evoked by the visual stimulation, which are pushed into the pipe by the source module. The feature extraction module produces features that are fed into the translation algorithm, which delivers a device command to the application, the latter gives audible feedback to subject.

4. Performance of the Task

The subjects sat on a chair with the forehead 50 cm from the centre of the computer screen. The subject was instructed to "dial" his/her phone number, birth date, and the numbers from one to nine, by gazing at the different numbered squares on the computer screen. Regarding the visual stimulation the subjects were asked to focus their attention on the number in the centre of the square. Subjects were instructed to pass to the next number after they heard a spoken number, whether or not it matched with the desired. Each phone number and birth date was dialed three times and numbers from one to nine were dialed four times, giving a total of 81-85 numbers depending on the phone number and if the month of birth had one or two digits.

5. Feature Extraction and Classification

Feature extraction and detection was controlled by a modular C^{++} software system, developed at Aalborg University, running on a Windows XP platform (see appendix 3). FFT power spectrum was performed, with an FFT number equal to 2048 (~4 s segments). Fourteen frequency bins, [5, 10.63, 7.08, 7.73, 8.5, 10.63, 12.14, 14.16, 15.4, 17, 21.2, 23.4, 24.4, 9.44], were picked from the power spectrum of each trial. From these frequencies the two highest peaks along with its respective frequencies form the feature vector. The classification procedure was performed according to the classifier described in Section C, with one sole difference: the stimulating frequency corresponding to block number 9 was changed from 21.25 Hz to 9.44 Hz, thus, the system would recognize the number 9 when the highest peak correspond to 9.44 Hz.

TABLE III.
SSVEP detection results from 7 healthy subjects using an online SS-VEP based BCI system. Subject 4 was only female subject, and subject 6 and 7 had myopia corrected with glasses. Detections are percentage correct classifications of all recorded segments. Signaling speed is in symbols/minute. Information Transfer Rate (ITR) is in bits/min.

Subject	Detections	Sig. speed $[min^{-1}]$	ITR [b/min]
Sub.1	94.15 %	8.3	22.19
Sub.2	94.34 %	9	24.18
Sub.3	92.37 %	7.2	18.37
Sub.4	100 %	10.5	33.28
Sub.5	89.54 %	11.5	27.29
Sub.6	71.6 %	9	13.11
Sub.7	57.65 %	9.5	8.71
average	**79.74 %**	**9.29**	**21.0**

6. *The On-line Software*

The on-line system developed here was designed as a modularised system, and is described in Fig. 4. The source is the module in charge of retrieving the continuous EEG signal from the amplifier and pushing blocks of N samples into the pipe, which consists of three modules: feature extraction, translation algorithm (which includes the classification process and the translation of the classification result into a command which is meaningful to the application, known as device command) and application. The EEG blocks are processed by each module and passed to the next one, until it gets to the application module, which gives feedback to the user. Online extraction of SSVEP features and classification is accomplished by power spectral analysis using FFT-based non-averaged periodograms on 2048 samples. Symbol selection is based on the amplitudes in the first, second and third harmonics as described in Section C. If the amplitudes are below an empirically set threshold no symbol is selected and the next segment is analyzed with an overlap of 1024 samples. The subjects were given feedback as an auditory playback of the detected number using a sampled voice.

7. *Results*

Experimental results from 7 subjects showed that 79.7% [57.7-100%] of the trials were correctly detected and classified with an average signaling rate of 9.3 [7.2-11.5] characters per minute. The Information Transfer Rate (ITR), a measure of communication transfer speed and accuracy, was also calculated according to [3] and [5]. These results can be seen in Table III.

8. *Discussions*

The required training time is negligible when using SS-VEP as compared to methods using event-related desynchronization/synchronization (ERD/ERS), for instance, [3] and [7]. Additionally, relatively high ITR’s are possible. Our system reaches an average ITR over 7 subejcts of 21 b/min, the Berlin BCI, which is based in motor imagery, reaches an average ITR over 9 subjects of 12.8 b/min [13], the system developed at the Tsinghua University in Bijing, based on SS-VEP, shows an average ITR of 27.15 b/min over 13 subjects [6].

The detection algorithm was implemented using a strategy favoring true positive detections at the expense of speed, i.e. shorter EEG segments would give faster but poorer detection results with more false positives and amplitudes below the empirical threshold selected for each subject will not produce any output, avoiding again false positives but making slower decisions (the next segment is analyzed with an overlap of 1024 samples).

Possible approaches to make the system faster are: to use more than one channel for detection as done in [5], [6] and [14], use Independent Component Analysis to capture early activation (below 1-s) of visual evoked responses, as suggested by Samir et al. [14].

Using SS-VEP based BCI some control of eye movements is needed, although we have experienced that attention without direct gazing can be used, as also reported by Kelly et al. and Allison et al [8], [9]. SS-VEP is a fast and “ready to use” communication tool for patients impaired by e.g. stroke or lesions on the spinal level.

9. *Conclusion*

The studies presented herein confirm that a simple yet relatively fast BCI can be obtained using the synchronized method of SS-VEP utilizing EEG as a command signal and using standard programmable equipment. One of the major challenges in systems using EEG based command signals is the rather low information transfer rates from 12.8 b/min using a motor imagery based BCI-system [13] and up to 68 b/min for SS-VEP based systems (one subject who was familiar with the system) [5]. Achievement of greater speed and accuracy depends on improvements in signal processing, translation algorithms, and in certain cases user training. These improvements depend on increased interdisciplinary cooperation between neuroscientists, engineers, psychologists, and rehabilitation specialists

The EEG has already shown to be a useful command signal for disabled without motor functions and thus no alternative signaling capabilities. Future work will very likely improve the signaling speed and the controlling paradigms and develop new assisting devices**.**

E. APPLICATIONS NOW AND IN THE FUTURE

The current efforts on the SS-VEP BCI are directed towards the implementation of an electric wheelchair with a portable computer mounted, whose screen will present to the patient with the BCI's Graphic User Interface (GUI). Two applications are being implemented for this SS-VEP controlled wheelchair, to provide communication and transportation means to persons with disabilities. For the communication purposes a "multi-tap" alphabet (like those used for text messaging in mobile phones) in connection with a Predictive Text Writer (PTW) has been designed in order to speed up the information transfer rate and promote an efficient communication tool for patients. On the other hand, for transportation purposes, an autonomous wheelchair is being designed, which will be able localize it self within a know environment and mobilize the patient to any desired location within the facilities, we have named this application wheelchair Navigation (WN). These two applications are being developed in an interdisciplinary effort by the Center for Sensory-Motor Interaction (SMI), the Intelligent Multimedia (IMM) Department and the Control Department of the Aalborg University. An overview of the complete BCI system, that has been called Device for Communication and Transportation Purposes (DCTP), and the state of both applications are described in the following subsections.

1. Device for Communication and Transportation Purposes (DCTP)

The hardware of the DCTP consists of four main components: the EEG acquisition system, an electric wheel, a portable computer and different kind of sensors, as shown in Fig. 5. All of them interact with each other in different ways depending on the application being used. The software of the DCTP is constituted of the BCI, PTW and WN programs. The former has been described in detail is previous section and the two latter will be described in the present one. The portable computer hosts the software that controls the BCI system and the applications, which are controlled by the EEG activity acquired by the EEG acquisition system. Trough the applications the electric wheelchair and the PTW are controlled providing the patient with communication and mobilization means. The sensors have the function of delivering feedback to system concerning the positioning of the wheelchair and its trajectory.

The main menu of the DCTP consists of three blocks flickering at different frequencies, as shown in Fig. 6. The size of the block is 2x2 cm. and the separation among them will depend on the number of blocks used, in this case only three blocks are used, but up to nine blocks can be used, what would provide 8 different applications in one Menu or several more if sub-menus are added.

The two blocks on top are shortcuts for the PTW and the WN and the block on the bottom switches on/off the entire system. When the system is initialized the on/off switch looks likes in Fig. 6a, with the 'off' text underneath the block stress in red letters and the 'on' text above the block written in dark letters. At this point the EEG signals are being monitored, features are extracted (FFT power spectrum) and classified but no action is taken unless the stimulation frequency of the switch block if found to be the main component in three consecutive one second FFT spectra; the system is in standby.

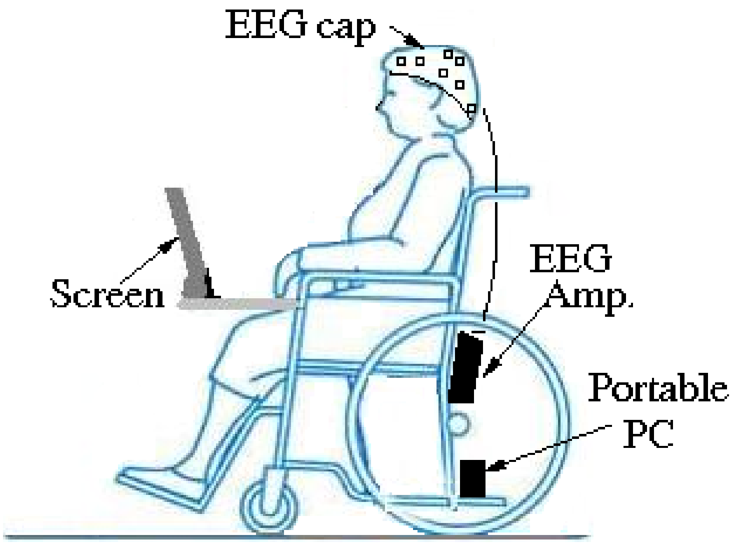

Figure 5: The DCTP system. The subject is sited on the electric wheelchair which serves as support for the PC and EEG acquisition system. The EEG cap is connected to the EEG amplifier which is connected to the PC via USB. The screen displays the GUI of the BCI and its applications. The location and type of the sensors has still not been settled since the WN application is in development.

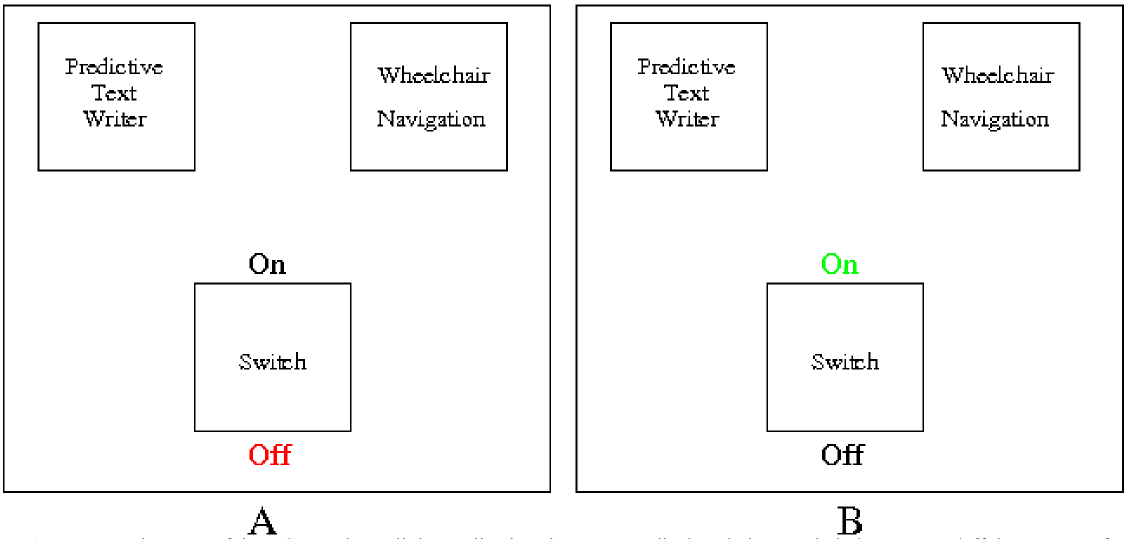

Figure 6: Main menu of the DCTP, where all the application shortcuts are displayed plus a switch that turns on/off the system. If more applications are developed, the number of blocks will grow accordingly. A) Main menu where the system is off or in standby, as the text underneath the switch block shows in red letters. B) Main menu where the system is on, as the text above the switch block shows in green.

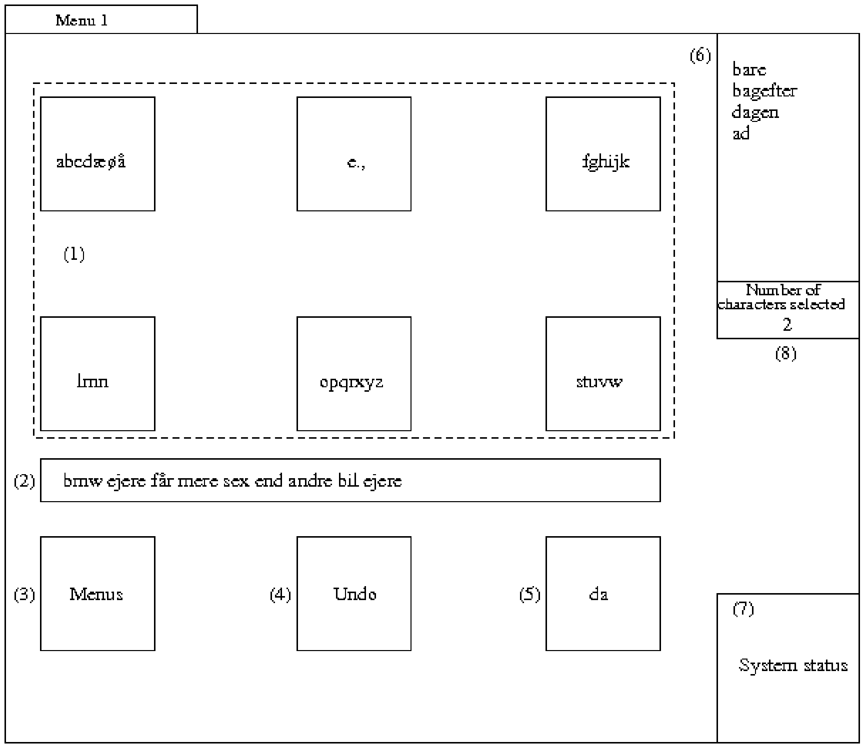

Figure 7: Menu 1. Is the initial menu presented, from where the subject can begin to write a text (Adapted from [10]).

If the system detects the switch block's stimulation frequency in three consecutive spectra the BCI is turn on, and actions will be taken if either of the three block's stimulation frequencies are found. At this time the switch block change its appearance, displaying the 'on' text above the block stress in green letters and the 'off' text underneath the block written in dark letters, as shown in Fig. 6b. From now on we will understand by 'detection' of a frequency the detection of a frequency component as the highest peak in three consecutive FFT spectra.

If the stimulation frequency of the PTW block is detected a new window pops up, displaying the PTW's GUI. If the stimulation frequency of the WN block is detected a new window pops up, displaying the WN's GUI. Finally if the stimulation frequency of the switch block is detected the system goes back to standby.

2. Predictive Text Writer (PTW)

The PTW[1] described in this section has been designed to enable a user to write text using a BCI system and a speech synthesizer to convert text to speech [10]. The language model has been trained using the 'Korpus 2000', which is a Danish corpus from the *Danish Language and Literature Society*. The PTW's GUI is divided into five menus; each of them displays nine flickering blocks:

[1] The PTW has been developed by Laust bach Larsen and Mads Torp Jacobsen whom have been supervised by Paul Dalsgaars and Zhang Hau Tan during an IMM 8th semester project proposed by Alvaro Fuentes Cabrera and Kim Dremstrup [10]

Menu 1: Word Prediction
Menu 2: Word Selection
Menu 3: Character prediction
Menu 4: Character selection
Menu 5: Show all text

As an example **Menu 1**, which is the main menu, is depicted in Fig. 7. Nine interactive blocks and three feedback text blocks are the components of this menu. Eight interactive blocks provide different functionalities to the user and the last block is used to shift between menus. The three feedback text blocks display information related with the state of the system, the text written so far and a prediction list.

Fig.7is divided into 7 parts, each of them denoted with round parenthesis (), which are described as follow:

(1) Six character blocks which cover the whole Danish alphabet
(2) Output text field which shows the last part of the written text
(3) Shift to the menus window, where the user can choose to go to any of the above described menus or go back to the main DCTP menu depicted in Fig.6.
(4) Undo block
(5) Prediction block showing the word with the highest probability of being next in the sentence
(6) Prediction list showing the next four words with highest probability of being the next in the sentence
(7) Text field used by the PTW to give feedback to the user in case of system errors
(8) Text field showing the number of character in the word selected by the user

Every time the user selects a character block a new prediction is performed and the prediction block and prediction lists are updated.
The PTW is in development and at present time a complete analysis and design of the PTW and the GUI has been carried out. So far only the PTW has been implemented. For a complete description of all menus and the PTW see [10].

3. *Wheelchair Navigation (WN)*

The WN[2] application is intended to control a wheel chair in a known environment, i.e. the house, apartment or working place of an individual with motor disabilities. The main WN GUI, shown in Fig.8, contains a floor plan of the place, a 'GO/STOP' block, which gives the command to start moving after selecting the desired location or stops the wheelchair if is already in movement, and a 'MAIN MENU' block which shifts to the main DCTP menu depicted in Fig.6. Each of the rooms in the floorplan contains a block with the name of the room which flickers at a certain frequency. The subject will gaze at the room he/she wants to go, and the translation device of the BCI system will detect the stimulating frequency of the room the subject is gazing at, a device command then is sent to the WN application and the wheel chair will take the subject to the desired location.

The wheel chair should be able to:

a) Location Algorithm: locate it self within the chosen environment, i.e. whether it is in the kitchen, the toilet or one of the rooms, and in which part of the specific room, i.e. close to the door or behind the table..
b) Path Planning: after receiving a command from the translation device, the wheel chair should be able to find the route from the current position to the desired location (path planning).
c) Obstacle Avoiding: avoid any obstacles that might be on the way, either objects that are not usually in the trajectory, i.e. toys, boxes, etc. or objects that are usually placed in a determined position, i.e. a coffee table, a desk, etc.

At present time the location algorithm, path planning and obstacle avoiding have being designed and implemented in Simulink using a LegoBot as a model of the wheelchair. The next step is the implementation of the control for the actual electric wheelchair.

4. *Future Applications*

In the future applications like sending text messages using mobile phones and web browser are contemplated to wider the range of communication alternatives for person with disabilities. These applications will be developed in an interdisciplinary framework which consists of professionals from the Intelligent Multimedia specialization, IT department and Center for Sensory-Motor Interaction of the Aalborg University.

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[2] The WN is being developed by Jeppe Møller Holm and Søren Lynge Pedersen under the supervision of Anders La Cour-Harbo during a 9th-10th semester project proposed by Alvaro Fuentes Cabrera, Omar Feix Do Nascimento and Kim Dremstrup.

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WN: Jeppe Møller Holm and Søren Lynge Pedersen under the supervision of Anders La Cour-Harbo

PTW: Laust bach Larsen and Mads Torp Jacobsen whom had been supervised by Paul Dalsgaard and Zhang Hau Tan

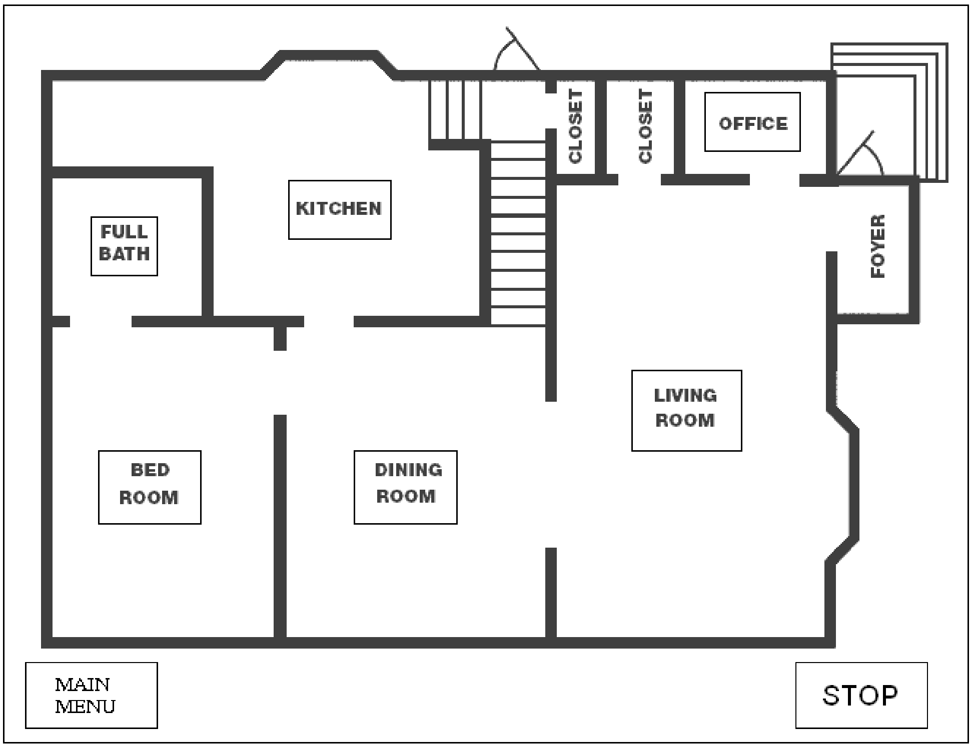

Figure 8: Floor plan of an apartment displayed on the screen for the subject to choose the room that the wheel chair should take him to. Each block containing the name of the room flickers at a specific frequency, which is recognized by the translation algorithm which sends the device command to the WN application to transport the wheel chair to the selected position. The block labelled stop can be used to stop the wheelchair at any desired moment if is in movement. The same STOP block will switch to GO if the wheelchair is still, and it will be used to give the command to start the movement after a location has been selected. The block on the left bottom shifts to the main DCTP menu depicted in Fig. 6.

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APPENDICES

App1 *ADDITIONAL TABLES FROM SECTION B. EEG SPECTRA USING SINGLE AND BI-FREQUENCY STIMULATION*

This appendix contains tables from section B. EEG Spectra using Single and Bi-frequency Stimulation. Table A1 displays Results for single frequency stimulation and Table A2 displays results for bi-frequency stimulation.

TABLE A1
Results for single-frequency stimulation. The first two columns show the letter and its stimulation frequency and the three other columns show the elicited frequencies in the Oz electrode.

Sub.1	Stimulating		Hz / amplitude x 10exp7	
Letter	freq. [Hz]	Fundamental	1st harmonic	2nd harmonic
A	5		10 / 2.6	15 / 2.4
B	7.08	7.2 / 3.5	14.2 / 2.9	
C	7.73	7.8 / 2.2	15.4 / 2.8	
D	8.5	8.4 / 1.01		
E	10.63	10.6 / 0.52		
F	12.14	12 / 0.97		
G	14.16	14.2 / 2.03		
H	17	17 / 1.44		
I	21.25	21.1 / 0.53		
Sub.2	Stimulating		Hz / amplitude x 10exp7	
Letter	freq. [Hz]	Fundamental	1st harmonic	2nd harmonic
A	5	5 / 2.84	10 / 1.68	15 / 1.54
B	7.08	7.2 / 2.05	14.2 / 3.94	
C	7.73	7.8 / 1.28	15.4 / 3.28	
D	8.5	8.4 / 4.2		
E	10.63	10.6 / 4.01		
F	12.14	12.2 / 3.2		
G	14.16	14.2 / 0.16	6.8 / 1.5	
H	17	17 / 3.82		
I	21.25	21.2 / 2.56		
Sub.3	Stimulating		Hz / amplitude x 10exp7	
Letter	freq. [Hz]	Fundamental	1st harmonic	2nd harmonic
A	5			15 / 5.75
B	7.08	7 / 5.05	14.2 / 2.73	21.2 / 2
C	7.73	7.8 / 9.05	15.4 / 2.66	23.2 / 1.37
D	8.5	8.4 / 3.07		
E	10.63	10.6 / 6.17	21.2 / 2.1	
F	12.14	12.2 / 1.96	24.2 / 3.15	
G	14.16	14.2 / 1.07	6.6 / 0.97	
H	17	17 / 1.62		
I	21.25	21.4 / 0.66		

TABLE A2

Results for bi-frequency stimulation. The first two columns show the letter and its stimulation frequencies and the other column shows the elicited frequencies in the Oz electrode.

Sub.1 Letter	Stimulating freq. [Hz]	elicited freq. Hz / amplitude x 10exp6
A	6.8 - 10.63	6.8 / 10.6
B	6.07 - 6.8	6 / 10.8 - 6.8 / 6.6
C	6.8 - 9.44	6.8 / 5.3 - 9.6 / 8.05
D	8.1 - 10.63	8.2 / 6.2 - 10.4 / 5.85
E	6.07 - 8.1	6 / 7.5 - 8 / 8.1
F	8.1 - 9.44	
G	10 - 10.63	10 / 10
H	6.07 - 10	6.4 / 10
I	9.44 - 10	
Sub.2 Letter	**Stimulating freq. [Hz]**	**elicited freq. Hz / amplitude x 10exp7**
A	6.8 - 10.63	6.8 / 1.67 - 10.6 / 2.15
B	6.07 - 6.8	6.8 / 5.08
C	6.8 - 9.44	6.8 / 5.1 - 9.4 / 2.97
D	8.1 - 10.63	8 / 1.8 - 10.6 / 1.6
E	6.07 - 8.1	8.2 / 3.8
F	8.1 - 9.44	8 / 3.25
G	10 - 10.63	10 / 2.7
H	6.07 - 10	10 / 2.23
I	9.44 - 10	9.4 / 1.43 - 10 / 1.44
Sub.3 Letter	**Stimulating freq. [Hz]**	**elicited freq. Hz / amplitude x 10exp7**
A	6.8 - 10.63	6.8 / 3.15 - 10.6 / 5.76
B	6.07 - 6.8	6.8 / 4.9
C	6.8 - 9.44	6.8 / 3.17
D	8.1 - 10.63	10.6 / 4
E	6.07 - 8.1	8 / 2.55
F	8.1 - 9.44	8 / 6 - 9.4 / 3.4
G	10 - 10.63	10 / 1.81
H	6.07 - 10	10 / 2.7
I	9.44 - 10	10 / 3

App2 *ADDITIONAL TABLES FROM SECTION C.* DEVELOPMENT OF THE CLASSIFIER

This appendix contains additional tables from section C. Development of the Classifier. Tables A3 and A4 display classification rates for each stimulation frequency. Tables A5 and A6 display classification rates for each subject.

TABLE A3
Results for 5 seconds of EEG signal over 7 subjects (average accuracy). The numbers in the first column correspond to the frequency the subject looked at. The numbers in the first row correspond to the number recognized by the BCI system.

5 s	5 Hz	7.08 Hz	7.73 Hz	8.5 Hz	10.63 Hz	12.14 Hz	14.16 Hz	17 Hz	21.25 Hz
5 Hz	**100%**								
7.08 Hz		**89.8%**			4.08%		4.08%		2.04%
7.73 Hz		2.27%	**95.46%**		2.27%				
8.5 Hz			2.27%	**97.73%**					
10.63 Hz					**100%**				
12.14 Hz						**100%**			
14.16 Hz	2.04%	2.04%	4.09%	2.04%	2.04%		**87.75%**		
17 Hz	6.82%	2.27%		2.27%				**88.64%**	
21.25 Hz	9,1 %	4.54%			11.36%				**75%**

TABLE A4
Results for 3 seconds of EEG signal, over 7 subjects (average accuracy). The numbers in the first column correspond to the frequency the subject looked at. The numbers in the first row correspond to the number recognized by the BCI system.

3 s	5 Hz	7.08 Hz	7.73 Hz	8.5 Hz	10.63 Hz	12.14 Hz	14.16 Hz	17 Hz	21.25 Hz
5 Hz	**93.19%**	2.27%		2.27%	2.27%				
7.08 Hz		**89.8%**			4.08%		4.08%		
7.73 Hz		4.55%	**90.9%**		4.55%				
8.5 Hz				**100%**					
10.63 Hz	1.85%				**98.15%**				
12.14 Hz					2.27%	**97.73%**			
14.16 Hz	2.04%	16.32%	4.08%				**77.76%**		
17 Hz		2.27%	2.27%	2.27%				**93.19%**	
21.25 Hz		11.36%			13.63%			2.27	**72.74%**

TABLE A5

Individual results using 5 seconds of EEG signal. The average accuracy for each character is shown as well as the average accuracy over the 9 characters.

5s	5 Hz	7.08 Hz	7.73 Hz	8.5 Hz	10.63 Hz	12.14 Hz	14.16 Hz	17 Hz	21.25 Hz	**Total**
Sub.1	100%	85.7%	100%	100%	100%	100%	100%	100%	100%	**98.4%**
Sub.2	100%	100%	100%	100%	100%	100%	100%	100%	57.2%	**95.2%**
Sub.3	100%	57.1%	85.7%	100%	100%	100%	100%	100%	100%	**93.1%**
Sub.4	100%	100%	100%	100%	100%	100%	85.7%	100%	50%	**93.1%**
Sub.5	100%	85.7%	100%	100%	100%	100%	100%	100%	100%	**98.2%**
Sub.6	100%	100%	100%	83.3%	100%	100%	100%	100%	100%	**98.2%**
Sub.7	100%	100%	83.3%	100%	100%	100%	28.6%	16.6%	16.6%	**75.9%**

TABLE A6

Individual results using 3 seconds of EEG signal. The average accuracy for each character is shown as well as the average accuracy over the 9 characters.

3s	5 Hz	7.08 Hz	7.73 Hz	8.5 Hz	10.63 Hz	12.14 Hz	14.16 Hz	17 Hz	21.25 Hz	**Total**
Sub.1	100%	85.7%	100%	100%	100%	100%	100%	100%	100%	**98.4%**
Sub.2	100%	100%	100%	100%	100%	100%	100%	100%	42.87%	**93.7%**
Sub.3	66.6%	71.4%	66.6%	100%	100%	100%	100%	100%	83.3%	**86.2%**
Sub.4	100%	100%	100%	100%	100%	100%	71.4%	100%	33.3%	**89.7%**
Sub.5	83.3%	85.7%	100%	100%	87.5%	100%	85.7%	100%	100%	**93.1%**
Sub.6	100%	100%	71.4%	100%	100%	100%	85.7%	100%	100%	**96.6%**
Sub.7	100%	100%	83.3%	100%	100%	83.3%	14.3%	16.6%	16.6%	**72.4%**

App3 *GUI OF THE ACQUISITION SYSTEM OF THE REAL TIME BCI.*

The stimulation program was developed on visual C running on Windows XP and it is based on the NetReader software provided by Neuroscan for its EEG acquisition systems and it functions together whit Scan 4.3 software. For a user guide of NetReader and Scan 4.3 please refer to the Neuroscan documentation.

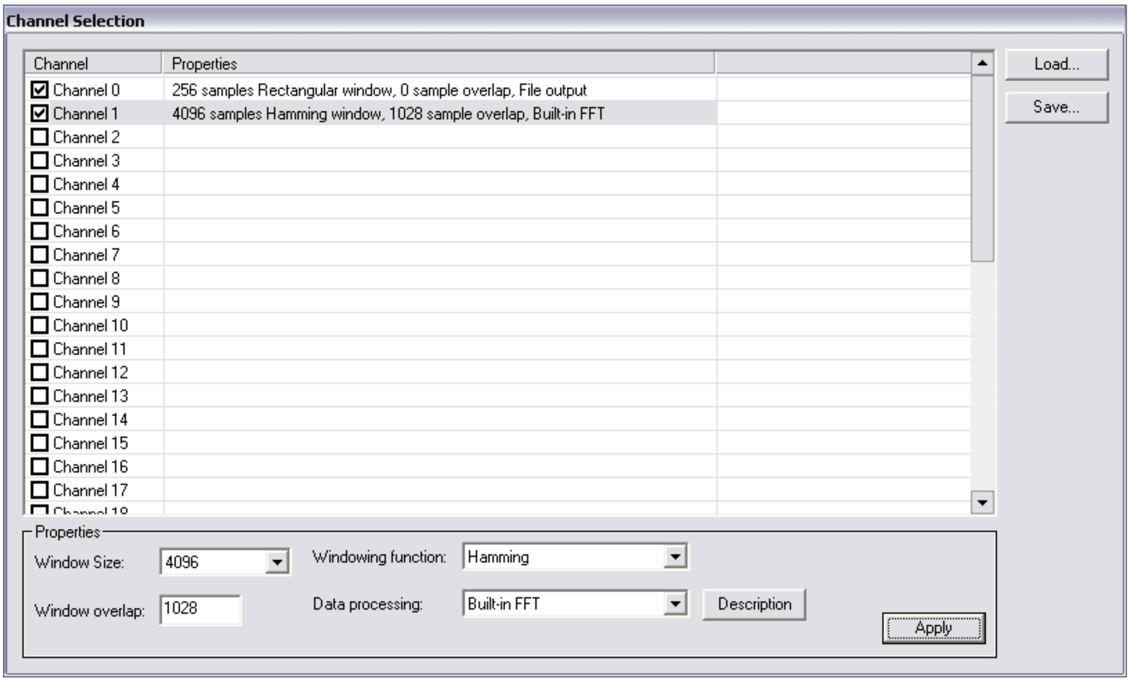

Figure A1: GUI of the acquisition system of the BCI.

Several channels can be selected, as shown in Fig. A1. Each channel has independent settings (except sampling rate that is set in *Acquire*), such as:

- Window size: a size in power of 2, from 32 to 4096. Other window sizes can be also added, if needed;
- Window overlap: set how many samples from current window are included at the beginning of the next window;
- Windowing function: select between *Rectangular*, *Hamming*, *Blackman*, *Flat Top* and *Hann* windows. Other functions can be added, if needed.
- Data processing function: lets the user choose between the '*Built-in FFT'* function, *'File output', 'Discard data'* and other data processing functions. If some valid .DLL libraries are found during program start, they are also added to the list. A description of the selected function can be viewed by pressing *Description* button.

Only checked (enabled) channels can be edited. Summaries of their settings are shown in the channel list, as shown in the figure.
Channel settings can be saved to and loaded from a *.ini* file.
During data acquisition the enabled channels receive data samples. Data buffers are provided for each channel. When the number of received samples becomes

equal to the window size of a particular channel, the selected windowing function is applied and selected data processing function is called. A circular buffer is implemented in order to minimize data moving overhead.

App4 *VISUAL STIMULATION PROGRAM*

The stimulation program was developed on visual C running on Windows Xp. The program is constituted of a dynamic-link library (VisualStimmDLL.dll) an executable file (GUI.exe) and a folder with several text files (Exp1). Place the GUI.exe and the Exp1 folder in the C: drive, the VisualStimmDLL.dll in C:\WINDOWS\SYSTEM32. The VisualStimmDLL.dll dynamic-link library was developed by Judex DataSystems and modified by Casino et al. and the executable file GUI.exe was developed by Wahoun et al. [1] (they do not to work on Windows 95/98). Using DirectX on WindowsXP it was possible to control the content of the monitor at the refresh rate of the screen enabling the programmer to set any pixel of the screen at any refresh cycle to a specific color. This program uses a setup file, with extension txt, to obtain the necessary parameters to run. This setup files must be placed in \c:/Exp1/". An example of a setup file is shown next:

```
numBlocks = 2
#
BiF r; Letter = A
Nred = (1; 9; 1; 10); Ngreen = (1; 6; 1; 7)
P os = (100; 000; 100; 100)
#
BiF r; Letter = B
Nred = (1; 9; 1; 10); Ngreen = (1; 5; 1; 5)
Pos = (400; 000; 100; 100)
#
```

The parameters in the setup file are explained as follow:

- numBlocks specifies the number of blocks that will appear on the screen, the same number of blocks must be describe in the setup file.
- BiFr specifies that this is a block using multi frequency stimulation.
- Letter=A specifies the letter shown inside the block.
- Nred=(Non1;Noff1;Non2;Noff2) specifies the frequency content of the red stimulation signal, where the stimulation frequency is fs= RR/(Non+Noff), whit RR=refresh Rate of the screen.
- Ngreen=(Non1;Noff1;Non2;Noff2) specifies the frequency content of the green stimulation signal, where the stimulation frequency is fs= RR/(Non+Noff), whit RR=refresh Rate of the screen.
- Pos=(x;y;width;height) specifies the position on the monitor and the size of the block.

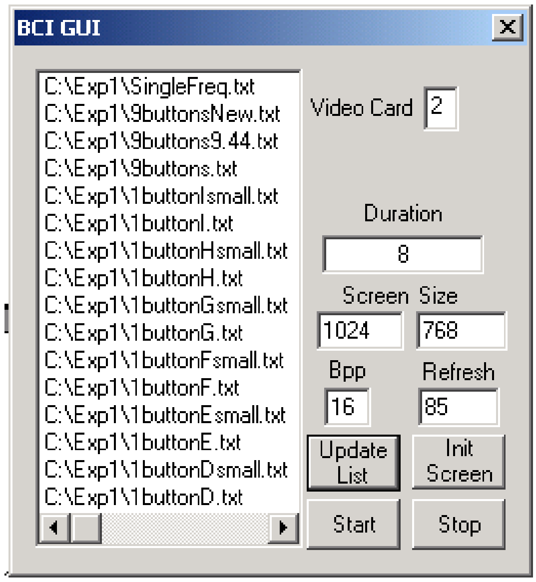

Figure A2: GUI of the visual stimulator.

Using specific functions in the DirectX interface it is possible to generate rectangular blocks of specific colors, which turn on or o at specific refresh cycles, this way different frequencies can be obtained by changing the number of *on* cycles and *off* cycles. As explained before Non and Noff are the number of refresh cycles that the block is *on* and *off* respectively to obtain a specific frequency. All these stimulation frequencies have 50 % duty cycle.
When the program is executed (GUI.exe) the window showed in Figure A2 appears, where it is possible to set the following:

- Video Card: selects which monitor will give the visual stimuli (in case that two monitors are connected to the computer), 1 is the main screen and 2 is the secondary screen, selecting 2 the stimulation will be delivered through the secondary screen and the program will be controlled on the main screen.
- Duration: Sets the duration of the stimulation in seconds.
- Screen Size: Is the screen resolution of the output monitor (default is 1024x768 pixels)
- Bpp: Determines the number of bits per pixel (default is 8)
- Refresh: Sets the refresh rate of the output monitor.
- Update List: Press this button to update the list of setup files in \C:/Exp1/".
- Init Screen Press this button to initialize the output screen.
- Setup File: The setup File can be selected in the text field located on the left side of the GUI window.
- Start: Press this button to start the visual stimulation (after the setup file is selected).
- Stop Press this button to stop the visual stimulation.

This program is only able to produce bi-frequency stimulation. However it is possible to give single frequency stimulation by setting the two stimulation frequencies to the same number.

EOD

Chapter 5

Auditory and Spatial Navigation Imagery in Brain Computer Interface using Optimized Wavelets

5.1 Erratum to "Auditory and Spatial Navigation Imagery in Brain Computer Interface using Optimized Wavelets" J Neurosci Methods 174 (2008) 135-146

Chapter 6

Comparison of Feature Selection and Classification methods for a Brain-Computer Interface driven by Non-Motor Imagery